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The Development and Validation of the Emporium Model Motivation Scale (EMMS)

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To the Graduate Council:

I am submitting herewith a dissertation written by Terry O. Gibson Jr. entitled "The Development and Validation of the Emporium Model Motivation Scale (EMMS)." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Educational Psychology and Research.

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The Development and Validation of the Emporium Model Motivation Scale (EMMS)

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Terry Odell Gibson Jr.
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DEDICATION

I dedicate this dissertation to my Mom (Patricia) and Dad (Terry).

They are the most wonderful parents a person can have.

They have been very supportive, encouraging, and have shown me unconditional love.

Without them, this feat wouldn't be possible.

For that, I am grateful.

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ABSTRACT

The purpose of this research study was to begin the development and validation of a new survey instrument; the Emporium Model Motivation Scale (EMMS). The instrument is designed to be used as part of a more holistic evaluation of non-traditional student-centered mathematics courses or programs redesigned using the Emporium Model (E-Model). Research suggested that the design of the E-Model environment was better suited to help students become more autonomy-natured (Williams, 2016). The present research was rooted in Self-determination Theory (SDT), which asserted that all individuals had a natural desire to strive for *autonomy*, *competence*, and *relatedness* in their social environments (Ryan & Deci, 2000; 2017). The research study consisted of a random sample of $n = 463$ respondents from both a U.S. community college and 4-year public university. Results of an Exploratory Factor Analysis (EFA) produced four parsimonious factor solutions that showed potential to be valid, highly reliable with ($\omega > .70$) and replicable across other samples or populations. The factors were analyzed using Polychoric correlations, with Unweighted Least Squares (ULS) extraction and Promax rotation. Correlational analysis, MANOVA, ANOVA, and Standard Multiple Regression were performed with accurate and reliable standardized factor score estimates. Overall results revealed statistically significant differences between the two institutions of higher learning across levels of the EMMS factors. Further analyses revealed that age was a statistically significant predictor of the EMMS factors and that older respondents were more autonomous and receptive of the E-Model design for course instruction.

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LIST OF ABBREVIATIONS

ALEKS	Assessment and Learning in Knowledge Spaces
ANOVA	Analysis of Variance
BPNS	Basic Psychological Needs Satisfaction
CLS	Computer Learning System
CSCC	Cleveland State Community College
CSE	Core Structural Elements
CTE	Changing the Equation
EFA	Exploratory Factor Analysis
E-Model	Emporium Model
EMMS	Emporium Model Motivation Scale
JSCC	Jackson State Community College
LSM	Learning Support Mathematics
MANOVA	Multivariate Analysis of Variance
MC-SRLS	Meta-Cognitive Self-Regulated Learning Strategies
MSLQ	Motivated Strategies for Learning Questionnaire
NCAT	National Center for Academic Transformation
OSU	Ohio State University
PCR	Program in Course Redesign
SAT	Scholastic Aptitude Test
SDT	Self-Determination Theory
SRLS	Self-Regulated Learning Strategies
SOE	Strategic Operational Elements
STEM	Science Technology Engineering and Mathematics
TI	Traditional Intructional

CHAPTER 1: INTRODUCTION

Course redesign initiatives at colleges and universities across the country have been growing in popularity over the past two decades funded by a multi-million dollar grant through the Pew Charitable Trust managed by the Center for Academic Transformation (Twigg, 2015). The Center is currently the National Center for Academic Transformation ([NCAT], 2005). As an independent non-profit entity, the organization provides resources to institutions seeking to redesign courses or entire programs by utilizing technology as an essential component to help improve academic learning outcomes at reduced costs.

Since 1999, NCAT has worked with over 200 colleges and universities and initiated four national programs (A Summary of NCAT, 2005) as well as other state or system-based programs consisting of 195 redesign projects. Of these, 156 projects (80%) were completed, which showed 72% improvement in student learning with 28% showing no change as compared to the traditional mode of instruction and a 34% reduction in operational cost. These promising results and the availability of resources brought on a wave of course redesign enthusiast. This chapter will provide an introduction for the basis of this study, which includes an awareness of the statement of the problem, the purpose, and research hypotheses.

Of particular interest in the current research study are the Learning Support Mathematics (LSM) redesign courses and programs that were initiated through *Changing the Equation* (CTE), one of the four national programs initiated by NCAT (A Summary of NCAT, 2005). CTE was a significant program funded by the Bill and Melina Gates Foundation in 2009 that was completed in 2012 to specifically help 2-year colleges throughout the U.S. participate in redesign efforts of LSM sequence courses and programs using one of the six NCAT course redesign models, the Emporium Model (E-Model). Low retention and high failure rates in LSM courses and programs at colleges and universities across the country were motivating factors for seeking alternative solutions for improving student performance in LSM courses (Bonham & Boylan, 2012; Schak, 2017).

Initially, there were 38 participating CTE institutions. According to NCAT, 20 institutions were able to fully implement the E-Model, 12 institutions carried out plans, but had not fully implemented the E-Model, and six withdrew because they were not able to meet the program requirements. There were 10 essential components to implementing the E-Model. All components were to be utilized in order to achieve the success guaranteed by NCAT for improved student learning outcomes and reduced cost. According to NCAT, institutions that did not achieve the desired results did not follow all the recommended components for a fully implemented E-Model (How to Redesign, 2013).

A fully implemented E-Model was totally student-centered and a learning environment void of the traditional lecture style (for the most part) where students transitioned from being passive to active learners utilized interactive mathematics software that comprised the students' individualized curriculum using software such as Pearson's *MyMathLab, ALEK*, or *Hawks Learning System*. These colleges either designed E-Models with Fixed or Fixed/Flexible schedules for students (How to Redesign, 2013). Students enrolled in Fixed sections met in labs with a full-time instructor or they were enrolled in Fixed/Flexible sections in which they may have met for one or two hours in a fixed setting and had the convenience of completing other hours on their own time in a computer lab where they had access to either full-time instructors or trained tutors for assistance (Twigg, 2011).

Student-centered learning environments have been found to enhance students' performance in developmental mathematics (How to Redesign, 2013). Other research has found that individuals who exhibited more *autonomy*, *competence,* and *relatedness* in their social environments, tended to be more intrinsically motivated and performed better (Reeves & Lee, 2014; Shuttle et al., 2017). Moreover, self-regulation played a major role in a student-centered environments, given that students were expected to be more responsible and independent learners (Cho & Kim, 2013). Understanding more about how learning strategies can influence students' experiences in an E-Model environment can contribute to the shortage of literature in this area.

While the success of many of the redesigned programs were well documented on the NCAT site, issues related to affective factors for redesigning developmental mathematics programs were an "untapped" area of study (Bonham & Boylan, 2012). These factors included attitudes related to mathematics and technology use, motivation, self-efficacy, and personality types. Literature has been found detailing the relationship between students' attitudes toward mathematics and technology and how these attributes affect students' achievement (Korobili, Tioga, & Malabari, 2010; Ku, Harter, Liu, Thompson, & Cheng, 2007; Poker & Amok, 2009; Plano, & Gary, 2004). According to Liaw (2012) learning more about students' perceptions of learning in a web-based or computer-aided instructional environment would be an asset to the implementation and sustainability efforts of these courses.

Students who have had negative experiences with learning mathematics coupled with negative experiences using technology (as a learning component) would most likely have difficult learning experiences. Referring to an article written by Bandura (1997), Bonham and Boylan (2012) stated that "students' beliefs about the value of the learning experience, their expectations of success, and their enjoyment of it that will motivate them to engage material actively and persist in spite of initial failures" (p. 16). The researchers also recognized the rise in the use of different models at the two-year and four-year colleges that included technology use as a supplementary component to engage students on formative and summative assessments. They indicated that a "major disadvantage can be overreliance on the technology to deliver instruction with little or no intervention, even when students are experiencing difficulty" (p. 16). Therefore, an awareness of the potential effects that can exist between affective factors, mathematics achievement, and computer assist-learning environments should warrant the use of valid and reliable items of a survey instrument that can potentially provide more insight regarding the sustainability of the E-Model, given the pre-existing perceptions this group of students may have with mathematics and technology use.

Statement of the Problem

Developmental courses or programs using the E-Model design can present students with challenges that could affect their levels of motivation to succeed in cases where students might have had bad experiences using computers or interactive software (Miranda, 2014). The researcher, of the current research study, asserts that the E-Model learning environment is designed for the autonomous or self-determined learner (Legault, 2017; Ryan & Deci, 2017). These learners are goal oriented, better managers of their time, and users of learning strategies to help them succeed (Cho & Heron, 2015). They are learners who tend to exhibit higher levels of self-regulation of activities and those who have worked toward internalizing the value and usefulness of these activities to render the desired outcome (Cho & Heron, 2015). The higher levels of self-regulation are the extrinsic motivating factors of *identification* and *integration* (Deci & Ryan, 2000; 2017) that learners have internalized and deemed valuable and useful to them. The extrinsic motivating factors that were once the driving force of motivation to perform an activity (that would otherwise not be interesting to them) have become internalized over time to the extent that students believe the activities are valuable, useful, or important toward long-term success (Ryan & Deci, 2000; 2017). This belief is so internalized that the identification with the activities can be integrated to the extent that the activities exhibit satisfaction, interest, or enjoyment: the ultimate achievement of intrinsic motivation. An individual will reach this level of intrinsic motivation only when she/he has attained higher levels of *autonomy* and *competence* (Niemiec & Ryan, 2009; Ryan & Deci, 2000; 2017). The potential problematic issue of LSM learners in an E-Model environment is the lack of Basic Psychological Needs Satisfaction (BPNS; CSDT, 2019): *autonomy*, *competence*, and *relatedness*; these are the foundations of Self-Determination Theory (Deci, Vallerand, Pelletier, & Ryan, 1991; Ryan & Deci, 2017; Ryan & Powelson, 1991).

The format of the learning environment alone can have adverse effects on students' performance (Kargar, Tarmizi, & Bayat, 2010). Many of these students have initial negative preconceived notions about their abilities to learn mathematics in computer-assisted learning environments (Miranda, 2014) that mirrors an E-Model environment. Typically, these students have lower levels of intrinsic motivation and are more motivated by extrinsic factors (Cho & Heron, 2015).

The development of a survey instrument that contains items that can be validated and found to be reliable is needed to aid in the long-term sustainability of course redesign projects utilizing the E-Model to assess students' perceptions of whether she/he feels adequately prepared, has a connection to the learning environment, and increased autonomy to be successful at completing the LSM sequence courses or programs utilizing the E-Model. According to Twigg (2000), to assess the readiness of an institution to carry out a course redesign project, each institution had to complete both the *Institutional Readiness Criteria* and the *Course Readiness*

Criteria. Of particular interest in the current research study are the criteria that address students' attitudes and perceptions. The focuses are these Institutional Readiness Criteria: "Does the institution have a demonstrated commitment to learner-centered education? Has the institution made a commitment to learner readiness to engage in IT-based courses?" The Course Readiness Criteria focus is this: "Do the faculty members involved have an understanding of learning theory?" Having an instrument available that can serve as a tool to aid in course redesign sustainability is found to produce valid and reliable results can provide additional insight that can assist program administrators in decision making regarding the effectiveness of a program in terms of student success and students' perceptions of the effectiveness of the program. A lack of readiness in these areas can have adverse effects on students' attitudes and motivations to succeed and therefore result in untenable long-term course redesign outcomes.

While these readiness criteria are used as a basis for assessing course redesign readiness, NCAT mainly provides methods geared toward obtaining empirical results for assessing impact. These were comparison analysis such as conducting quasi-experiments, comparing completion rates as well as cost effective analysis. NCAT supports the use of assessing student satisfaction as a contributing factor in assessing program effectiveness, but there is no readily available survey instrument that has undergone validation that institutions can use to gather information regarding the perceptions of students enrolled in courses using the E-Model. Additionally, there is no guidance on providing means to develop an instrument to be used as an effective tool to administer to students. Individual institutions are left to decide how best to measure latent constructs.

NCAT does provide a plethora of information related to lessons learned from all three initial rounds of course redesign projects as well as provide information regarding other impacts on student success for future course redesign initiatives. An investigation of the Institutional Readiness Criterial: (7. "The institution must have established ways to assess and provide for learners' readiness to engage in instructional technology-based courses.") revealed that some institutions utilized a form of a survey instrument to assess students' attitudes regarding students' experiences. However, this was not a required component of measuring the effectiveness of the E-Model. For example, six of the 20 colleges that implemented an E-Model indicated that some form of a survey was administered to gain information about students' attitudes of math and general student satisfaction information. Whether the items of the surveys used had undergone a process of validation and shown to be reliable was not reported (NCAT, 2005). Most provided comments on altered student attitudes regarding the E-Model. Nevertheless, while there is a relationship between affective and motivational measures, mathematics achievement, and computer use, there is an absence of research to address the influence that these phenomena have on students in terms of their perception of a model used to enhance the learning of developmental mathematics skills and concepts, which is significantly different from the traditional lecture approach.

Purpose of the Study

According to Twigg (2003), "a rigorous evaluation focused on learning outcomes as measured by student performance and achievement" was the method for evaluating course redesign models (p. 30). Therefore, the purpose of the current research study is to pilot test the development of a survey instrument designed to assess students' perceptions of the E-Model for course redesign that focuses on affective and motivational measures to provide a more complete assessment of the effectiveness of the E-Model used by 2-year colleges and universities across the nation to enhance students' performance in LSM courses and programs. More specifically, the current research study seeks to develop and validate a survey instrument that can potentially identify latent factors to aid in the sustainability efforts of the E-Model learning environment by learning more about students' BPNS, affect, and learning strategies used as a result of learning mathematics in a non-traditional learning environment. Additionally, the instrument would provide a means for LSM and non-LSM program administrators and faculty to explore ways of accommodating students by understanding more about how to foster an engaging student-centered environment through learning more about those extrinsically motivating factors that could potentially increase students' intrinsic motivation to engage in activities that they would otherwise not be interested.

Notably, several of the items to be adopted to form the EMMS were developed by the researcher and based on observations and discussions with students learning in a more student-centered learning environment. The researcher of the current study has 13 years of experience teaching at both a public university and community college with seven years of experience developing and facilitating student-centered learning environments similar to the E-Model design for course instruction at a community college for both LSM and non-LSM students. Additional information regarding the experience of the researcher can be found in Appendix G.

Hypotheses

1. The Emporium Model Motivation Scale would yield parsimonious factor solutions and be a valid measure of autonomous motivation.
2. The Emporium Model Motivation Scale would yield satisfactory internal consistency reliability of the factor solutions using Ordinal Omega Coefficient Alpha $\omega \geq .70$.

Research Questions

1. Are there differences in college on the EMMS factors?

2. Are there differences in type of course (Intermediate Algebra, College Algebra, Finite Mathematics, and Pre-Calculus) on the EMMS factors?
3. Are there differences in age on the EMMS factors?
4. Are there differences in semester on the EMMS factors?
5. Are college, course, age, and semester predictors of the EMMS factors?

Open-ended Response Items

Including qualitative or open-ended response items in a research study that is dominantly quantitative can enhance the interpretability of results (Bamberger, Rugh, & Mabry, 2012). To gain additional insights regarding the experiences of students' learning in the E-Model environment, two general open-ended items were added to the research study. These are: "Is there anything else that you would like to share regarding your learning experiences in the E-Model environment?" and " Additional comments:".

Significance of the Study

The current research is of significant importance because it seeks to fill a gap in the literature that has theoretical and practical implications. While SDT has broad underpinnings across spectrums of life that involves human development in families, education, work, and society in general (Ryan & Deci, 2017), there are certain aspects of the theory that have not been applied to LSM learners in an E-Model learning environment. The current research seeks to further extend SDT into an area of mathematics education that deals with the psychological aspects of understanding developmental mathematics learners' experiences in learning environments that use the E-Model design. More importantly, it seeks to address the rising failure rates of students completing LSM and non-LSM courses across the U.S. at institutions of higher learning offering courses or programs redesigned using the E-Model (Aly, 2016; Bahr, 2008; Chockla, 2013; Clyburn, 2013; Complete College America, 2012; Eckhardt, 2016; Fong, 2013; Patson, 2014). Because the researcher asserts that this type of learning environment is designed for the autonomous learner, SDT can be used to assess whether the E-Model course design satisfies students' BPNS of "autonomy, competence, and relatedness" that all individuals strive to achieve (Ryan & Deci, 2000, p. 65). Findings of the current research study can lead to further validation of items of the EMMS that can be used to generalize or extend to other populations using the E-Model design and add to the holistic body of work in SDT with respects to mathematics education.

On the other hand, the practical implications of the current research will fill a gap that researchers such as Bonham and Boylan (2012) say is lacking and others say have ambiguous results in terms of the effectiveness of LSM programs (Bettinger & Long, 2005). As previously mentioned, Bonham and Boylan (2012) indicated that learning more about students' affect, attitudes, and motivations were an unexploited area of study. The current research study can provide more insights about the effectiveness of courses or programs using the E-Model design that explores the psychological well-being of students given the significance of the correlations found between these psychological traits, student performance, and mathematics achievement (Cho & Heron, 2015; Kargar, Tarmizi, & Bayat, 2010; Ku et al., 2007; Skaalvik, Federizi, & Klassen, 2015). Furthermore, results of the current study could be of great significance to those interested in the sustainability efforts of the E-Model design. These are the school administrators, faculty, staff, and other stakeholders with a vested interest. Results can potentially inform stakeholders about the readiness of students to learn in an E-Model environment, determine whether there is a need to provide additional professional training for staff assigned to assist students in an E-Model environment, or address concerns that might hinder the basic psychological needs to function in such an autonomous learning environment.

Assumptions

Several assumptions must be addressed. The researcher assumed participants of the current research study were enrolled in or at least attempted to complete a gateway mathematics course or an LSM course or module offered using the E-Model design. The researcher assumed that each participating institution of higher learning maintained sustainability of the 10 steps of the E-Model course redesign at the time of the current study. The researcher also assumed that each participating institution of higher learning used trained individuals in addition to instructors to assist students in the computer labs and computer classrooms. It is assumed that each student used a CLS to complete her/his individualized curriculum. Lastly, the researcher assumed that each participating institution of higher learning maintained ongoing efforts to provide each student the necessary support needed to transition from a passive learning environment to one that is more active and student-centered, which included the use of technology as a critical component of the E-Model course design.

Delimitations

The current research study focuses specifically on students' experiences in a non-traditional student-centered learning environment. The researcher was inspired to study students' experiences in these modularized courses as a result of seven plus years working with LSM students in learning environments that were more student-centered that included the use of a CLS for which students had to complete their individualized curriculum. These learning environments mirrored the E-Model design and were composed of several components that were designed to transform the learning environment from one that was more passive and instructor-centered (TI approach) to one that promoted student-centered instruction through active student engagement to problem-solve while using technology to help students succeed in their college-level mathematics course(s) and beyond.

The course redesign movement was the result of NCAT's successful course redesign initiatives that spanned nearly 15 years starting in 1999 (Twigg, 2015). More specifically, the *Changing the Equation* initiative that started in 2009 was the motivation for the current research study. The *Changing the Equation* initiative focused on LSM course redesigns implemented at community colleges across the county using the E-Model design. The current research study seeks to learn more about the psychological well-being of students learning in an environment, using the E-Model design for course instruction. Researchers such as Mireles (2010) believes an investigation of these psychological aspects (i.e., the affect, motivations, and other perceptions related to attitudes, and self-efficacy) should be a part of an evaluation of the effectiveness of LSM courses and programs.

The current research study explores this "untapped" area of study to begin the validation process of a survey instrument designed to learn more about students' psychological well-being grounded in SDT. The theory forms the basis for the current research study that learning in an E-Model environment requires skills of an autonomous learner, which the EMMS was designed to measure. It is the hope of the researcher that the EMMS can be used as a tool for stakeholders to aid in sustainability efforts of the E-Model design used in both LSM and non-LSM modularized courses or programs. While there were 20 community colleges that successfully implemented the full E-Model methodology, 15 of those community colleges used an E-Model design with modularized curriculum using a fixed/flexible schedule (NCAT, 2005). However, only 11 of those 15 community colleges successfully implemented the E-Model course redesign

(NCAT, 2005). Therefore, the current research study will collect data from at least one of those 11 community colleges that had successfully implemented the E-Model design for LSM courses or programs. It is not necessary to obtain a national sample. The current research design focuses on the pilot phase of the validation process for items designed for the EMMS. Therefore, a validation method of factor generalization (e.g., Confirmatory Factor Analysis) will not be used in the current research study at this early stage. Additionally, the researcher is seeking to gain a random sample of actively enrolled students of the target population who at least attempted or completed an LSM modularized course or program over a short span of 2 years (i.e., from fall 2016 to spring 2018). The goal is to minimize the effects of maturation over time while maximizing the response rate, which is why the sample will not be random at this stage of the validation process.

Limitations

Several limitations are worth mentioning. Sample size is a major limitation of the current research study. A reduced sample size can affect the interpretation of analyses that will be used in the current study (i.e., Exploratory Factor Analysis-EFA), given that data participation is voluntary in the current research study. Other potential limitations will be concerning the use of specific independent and dependent variables to be used in analyses of the current study. Due to the possibility of unequal sample sizes, some independent variables may be collapsed or not used in analyses and other dependent variables may be too highly correlated to be used in specific analyses as well to satisfy assumptions. Another important limitation is concerning statistical assumptions that must be addressed prior to any analyses, which are discussed in detail in Chapter 3. Some statistical tests are not as sensitive to violations of assumptions as other tests are in the current research study. These violations will resort to the use of more stringent alpha values. However, other advanced analyses such as MANOVA will not be used if assumptions were to be severely violated. The researcher will result to using a less powerful analysis (i.e., multiple Between Subjects ANOVAs using Bonferroni adjustments and Tukey post hoc tests when necessary) to address research questions 1, 2 and 3.

Other noteworthy limitations to consider are history and maturation that could potentially affect the validity of results. Participants will be responding to a survey instrument regarding their experiences taking a course or being in a program for which they will have to recall experiences that might be at least a year old. Environmental and psychological factors could potentially influence results given that participants will be responding to the survey in their own environments, which responses will depend on their state of maturation at the time.

Terms and Definitions

Amotivation. "Amotivation is a state in which people lack the intention to behave, and thus lack motivation as that term is defined in the cognitive-motivational tradition" (Deci & Ryan, 2000, p. 237). Amotivated individuals are impersonal and are "lacking an intention to act" (Ryan & Deci, 2000, p. 61).

Autonomy. Autonomy is a term used to describe an individual who is self-driven, seeks for independence, and feels a sense of control or that she/he has a choice to engage in or complete an activity or task (Niemiec & Ryan, 2009; Ryan & Deci, 2000).

Competence. Competence is a term used to describe an individual who feels that she/he has the ability to perform well on an activity or task (Ryan & Deci, 2000) or individuals who "feel able to meet the challenges of their schoolwork" (Niemiec & Ryan, 2009).

Computer-based Learning Resources. Computer-based learning resources represent one of the six characteristics shared by all redesign models that refers to the use of "instructional software and other Web-based learning resources…tutorials, exercises, and low-stakes quizzes that provide frequent practice, feedback, and reinforcement of course concepts" (Twigg, 2003, p. 30).

Computer Learning System (CLS). A computer learning system is any interactive computer-software designed to supplement or deliver the mathematics curriculum, which includes adaptive-software designed specifically to individualize the students' experience learning mathematics. Some of the commonly used CLSs are Pearson's *MyMathLab*, *Carnegie Learning*, *Hawk's Learning System*, and *ALEKS* among others. It is noteworthy to mention that other earlier terms have been used to describe a broad range of CLSs. These were: computer-assisted instruction (CAI; Spradlin, 2009), and computer-based instruction (CBI; Kulik, Kulik, & Cohen, 1980)

Course Readiness Criteria (CRC). The CRCs represent a group of eight questions that NCAT used to gauge whether a course met the criteria to undergo a full-fledge course redesign using technology to enhance academic performance while reducing operational costs (Twigg, 2000).

Extrinsic Motivation. Extrinsic motivation is a term used to describe an individual who relies on external factors to drive them to engage in an activity or complete a task (e.g., getting good grades, to avoid a punishment, self-appraisal, for the value or worth; Ryan & Deci, 2000).

Identification. Identification (*identified regulation*) is one of the four regulatory styles on the continuum of extrinsic motivation (Deci & Ryan, 2000). The regulatory style reflects an individual who through internalization finds value in an activity or task or deems it important for achieving some goal or desired outcome (Niemiec & Ryan, 20009).

Institutional Readiness Criteria (IRC). The IRCs were a group of eight questions that NCAT used to determine whether an institution was ready to embark on a large-scale course redesign project using technology to enhance academic performance while reducing operational costs (Twigg, 2000).

Integration. Integration (*integrated regulation*) is the most autonomous of the four regulatory styles on the continuum of extrinsic motivation (Deci & Ryan, 2000). The regulatory style reflects an individual who through internalization has "fully transformed the regulation into their own so that it can emanate from their sense of self" (Ryan & Deci, 2000, p. 60).

Interactive-software. The term is used in the current research study to describe the CLS.

Internalization. "Internalization is the process of taking in a value or regulation…and describes how one's motivation for behavior can range from amotivation…to active personal commitment" (Ryan & Deci, 2000, p. 60).

Intrinsic Motivation. Intrinsic motivation is a term used to describe an individual who is driven to complete a task or engage in an activity because it is naturally "interesting" and "enjoyable" or results in a satisfying experience (Niemiec & Ryan, 2009; Ryan & Deci, 2000).

Learning Support Mathematics (LSM). LSM is a more modern term that describes any instructional material designed to help improve student learning of essential mathematical skills and concepts in preparation for taking college-level mathematics course(s). This term is synonymous to developmental mathematics defined by Spradlin (2009) to mean "courses and programs designed to provide the skills and knowledge for underprepared students to succeed in college-level mathematics courses" (p. 16).

Locus of Control. Locus of control (*perceived locus of causality*) describes the emanation process of a regulatory style. It indicates whether individuals have an external orientation (driven by rewards or punishment-controlled), internal orientation (driven by the self-more autonomous), or impersonality orientation (not motivated to act) (Deci & Ryan, 2000).

Maturation. Maturation refers to the possible changes in psychological factors of participants that can affect responses to items in a research study to the extent that this change affects the internal validity of the results due to passage of time (Fraenkel & Wallen, 2014).

On-demand help. On-demand help is one of the six characteristics shared by all redesign models to describe the assistance provided to each student through an “expanded support system” given that the traditional lecture in these models are replaced with “individual and small-group activities that take place either in computer labs-staffed by faculty, graduate teaching assistants (GTAs), and/or peer tutors-or online, enabling students to have more one-on-one assistance” (Twigg, 2003, p. 30).

Regulation. Regulation is a term used to describe an action by the individual during the internalization process.

Self-determination Theory (SDT). “SDT is an empirically based, organismic theory of human behavior and personality development…concerned with how social-contextual factors support or thwart people’s thriving through the satisfaction of their basic psychological needs for competence, relatedness, and autonomy” (Ryan & Deci, 2017, p. 3).

Self-regulation. Self-regulation is a term used to describe an individual who is driven by internal means through identified regulation, integrated regulation, or merely intrinsically motivated, and according to Zimmerman and Martinez-Pons (1990), these individuals are “active promoters of their academic achievement” (p. 51).

Traditional Instructional (TI). This term was adopted from Spradlin (2009), which refers to instruction that is delivered “face-to-face” in a classroom setting that includes a variety of instructional approaches (i.e., lecture, discussion, or group work).

Chapter Summary

The low completion and failure rates in LSM and non-LSM courses at the nation’s 2-year and 4-year colleges and universities resulted in high dropout rates, disappointment among students, and reduced enrollment in introductory college-level courses (Schak, 2017). The increased interest in redesigning mathematics courses and programs were the result of this growing problem, more so, at community colleges across the country (Chen, 2016). According to Belfield, Jenkins, and Lahr (2016), the implementation of course redesigns would not work, if efforts were not cost effective. The successful completion of program initiatives implemented by NCAT resulted in six redesign models that improved learning at reduced costs that included the use of a CLS as central to the success of the redesign models (Twigg, 2015).

The E-Model methodology proved to be one of the most implemented and effective course redesign models for addressing the issue of low retention and completion rates of students in LSM courses, particularly at community colleges nation-wide (Changing the Equation, 2012; Twigg, 2011). During this time, there were calls for more empirical and evidence-based research studies examining the effects that the E-Model methodology had on students’ psychological well-being (Bonham & Boylan, 2012). According to Chung (2005), “The most successful programs are theory based. They don’t just provide random intervention” (p. 2). The E-Model course redesign is a type of intervention best suited for developing self-determined learners (Williams, 2016).

Intervention models that provide students the opportunity to become self-determined learners have the potential to build students' confidence in their abilities to do mathematics and possibly increase their interest in the subject (Brey & Tangney, 2017). An autonomy-supportive learning environment promotes positive outcomes (Gagne, 2003). From a theoretical perspective, SDT is the underlying theory that is suitable for assessing the effectiveness of the E-Model methodology. The theory asserts that all individuals seek for autonomy, competence, and relatedness in their social environments (Ryan & Deci, 2000; 2017).

The underlying aim of the current research study is to examine whether the E-Model methodology is supportive of students' BPNS, which can be attempted by investigating the posed research questions and hypotheses. Later chapters will discuss the methodological design of the current research study, examine the results of the research questions and hypotheses, and conclude with a discussion of the results and implications. The following chapter will introduce literature that addresses key ideas from the previous chapter.

CHAPTER 2: LITERATURE REVIEW

The literature review begins with a discussion of SDT, which is the chosen theoretical framework that best describes the functionality of the E-Model methodology. The theory provides the basis for understanding whether the E-Model learning environment supports students' BPNS. The foundation of the E-Model is the NCAT methodology. A large portion of the review focuses on the NCAT methodology, the program initiatives that birth the existence of all six NCAT redesign models, and then focuses specifically on the E-Model methodology. As an alternative method to the TI approach, the review discusses how the E-Model methodology became a popular methodological instructional design at both 2-year and 4-year colleges and universities across the country after the launch of the CTE program initiative (Changing the Equation, 2012). The later part of the review discusses the 10 essential elements (i.e., the CSEs and SOEs) unique to the E-Model methodology; these elements are a result of the first program initiative, PCR (Twigg, 2011). Following that discussion, is a review of the latest literature that includes empirically-based evaluations and research studies that investigated the effects of the E-Model methodology on students' achievement and psychological health. The review concludes with a discussion of the role of the MC-SRLS as critical to building self-determined learners in the E-Model learning environment.

Theoretical Framework

There were several underlining theories that provided a framework for the development of the EMMS. The overarching theoretical framework of the current study is Self-Determination Theory (SDT). Ryan and Deci (2000) indicated that all individuals strive to achieve a sense of *autonomy* (to feel free and self-directed), *competence* (to feel capable of performing) and *relatedness* (to feel a sense of connection), which were the basic psychological needs to grow and function in society, referred to as the BPNS. Ryan and Deci (2000) identified a continuum of motivation that ranged from *amotivation* (lacking the motivation to act) to *intrinsic motivation* (one who experiences enjoyment of an action). Within those extremes were four levels of extrinsic motivation (i.e., the continuum of relative autonomy). Of those four levels, two were the most autonomous (*identification* and *integration*). The EMMS was designed to measure those more autonomous levels of extrinsic and intrinsic motivation. Figure 1 was adopted from Legault (2017, p. 4), which illustrated the internalization process of human motivation.

According to Legault (2017), SDT is "multidimensional" and composed of six mini theories. These theories describe how we relate to and connect with our social settings. Figure 1 displays the dimensionality of SDT on a continuum that illustrates the two extremes of motivation. The four degrees of extrinsic motivation are characteristics of organismic integration theory; one of the six mini theories (Legault, 2017; Ryan & Deci, 2017; Ryan & Deci, 2000). Legault (2017) asserts that at the core of the six theories is the need for individuals to attain a sense of autonomy, competence, and relatedness to thrive in society. The following excerpt briefly describes SDT in terms of the mini theories.

> The first mini-theory, *cognitive evaluation theory*, centers on the factors that shape intrinsic motivation by affecting perceived autonomy and competence. The second mini-theory is *organismic integration theory*, and it concerns extrinsic motivation and the manner in which it may be internalized. *Causality orientations* theory describes personality dispositions – that is, are individuals generally autonomous, controlled, or impersonal? The fourth mini-theory, *basic psychological need theory*, discusses the role of basic psychological needs in health and wellbeing and, importantly, outlines the manner in which social environments can neglect, thwart, or satisfy people's basic

> psychological needs. *Goal content theory* is concerned with how intrinsic and extrinsic goals influence health and wellness. Finally, *relationship motivation theory* is focused on the need to develop and maintain close relationships and describes how optimal relationships are those that help people satisfy their basic psychological needs for autonomy, competence, and relatedness. (p. 2)

In theory, self-determined students should thrive in an autonomy supportive learning environment (Gagne, 2003). If students who exhibited lower levels of autonomy were given the opportunity to learn mathematics in an autonomy supportive environment, then it opens the door for students to build confidence in their mathematical abilities and increase their enjoyment of learning the subject (Bray & Tangney, 2017). Over the duration of a course or program, students who initially were driven to learn by external factors could potentially regulate learning through the progression of internalization and come to value the importance of or ultimately enjoy a subject that they once thought was difficult to excel in (Ryan & Deci, 2000; 2017). When the learning environment stops being autonomy supportive, the result can "undermine" students' motivation, which could cause students to digress towards relying on external means to progress through the course or program or can hinder students' ability to thrive in the learning environment or worse, become amotivated (Bray & Tangney, 2017; Ryan & Deci, 2017). This viewpoint centered around whether the E-Model methodology was designed to support students' BPNS. The following is a detailed review of the NCAT methodology and how the E-Model methodology came into existence.

Development of the NCAT Methodology

According to NCAT there were seven programs offering course redesign projects spanning a period of 13 years since 1999. These included the *Programs in Course Redesign*

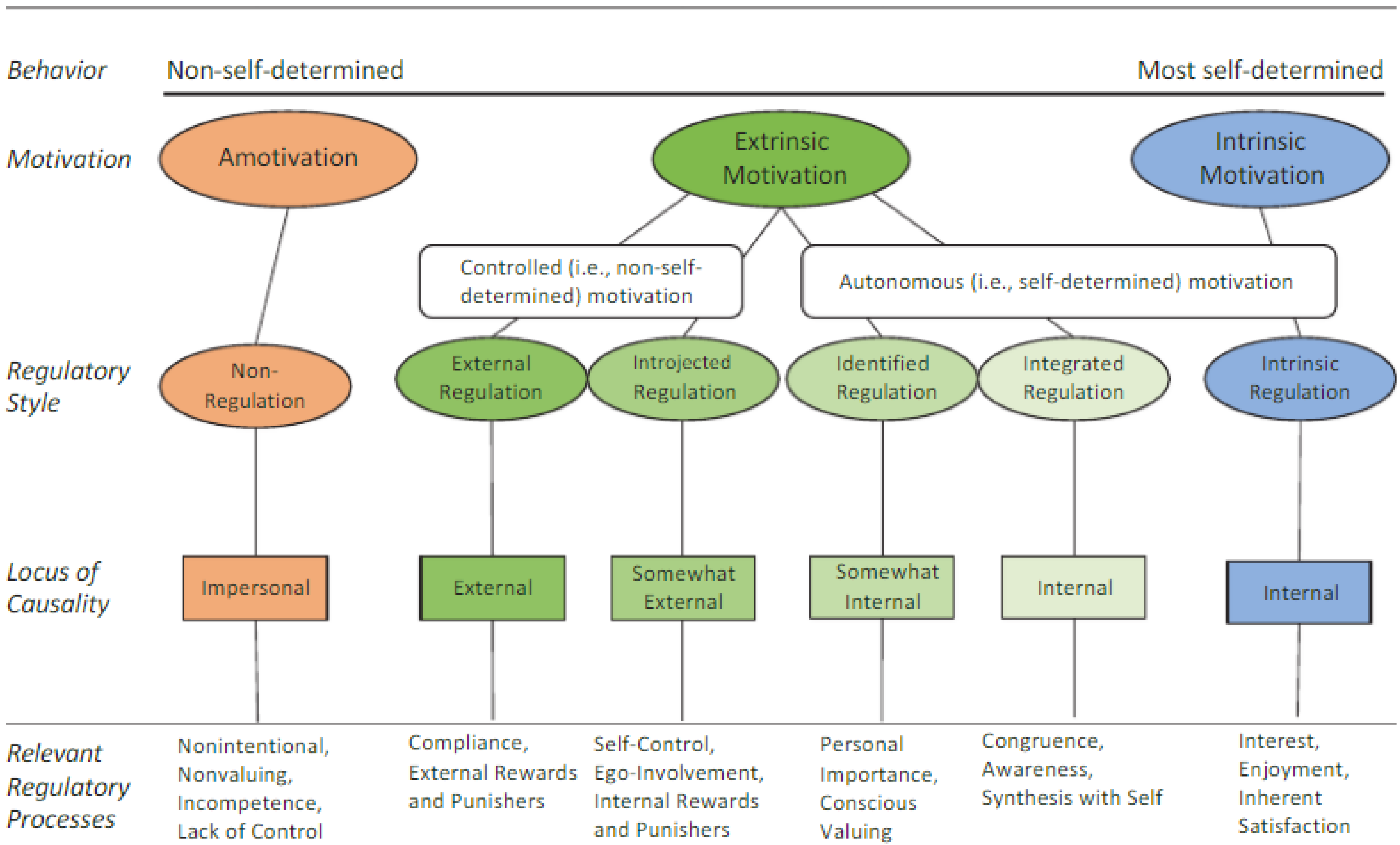

Figure 1: Self-Determination Theory: Continuum of Human Motivation

(PCR), *The Roadmap to Redesign, Increasing Success for Underserved Students, Colleagues Committed to Redesign*, *State and System Course Redesign*, *The Redesign Alliance*, and *Changing the Equation* (CTE). The existence of these programs grew from an interest to "redesign instruction using technology to achieve quality enhancements as well as cost savings" (p. 30) to support both 2-year and 4-year colleges and universities interested in providing high quality education at low costs (Twigg, 2003). The six redesign models were developed using a framework called the *Four-Stage Process*. This process involved a cyclical approach that consisted of *proof of concept*, *analysis*, *communication,* and *scale* (What We Do, 2005). The process laid the groundwork for implementing effective course redesign models. Models that were designed to improve student performance while using information technology to employ best practices from learning theory research to create student-centered learning environments.

Proof of concept. The success of the funded redesign program initiatives depended on the implementation of the four-stage process. The idea of proof-of-concept was the essence of the creation of the six learning models: "*supplemental*, *replacement*, *emporium*, *buffet*, *fully-online* and *linked workshop*" that have sustained the test of time. The success of the six course redesign models is proof-of-concept (the NCAT methodology).

Analyses. To demonstrate proof-of-concept, analysis was performed to provide supporting evidence suggesting the effectiveness of the models. Data were gathered and analyzed during the implementation phase of each program initiative. These analyses included student completion rates, cost effectiveness results, and comparison of student performances. The reporting of results also included attitudinal outcomes from some of the participating institutions. In addition, successful techniques were identified, used as essentials for implementation, and the sustainability of the redesign models.

Communication. To disseminate information regarding the success of the program initiatives, NCAT developed means to communicate the effectiveness of the different programs that were implemented at the time to promote and inform those who had an invested interest in the accomplishments of NCAT. Several forms of communication existed during this period. These forms of communication were through articles (Articles, 2005), monographs (Monographs, 2005), *The Learning MarketSpace* (The Learning MarketSpace, 2005); which was an electronic newsletter, and *What Others Are Saying about NCAT* (What Others Are Saying, 2005).

Scale. The cycle concluded with ways to streamline the outcomes from each program initiative. Collaboration from participating statewide systems, colleges, and universities helped NCAT develop a methodology that could be efficiently and effectively used by other institutions interested in implementing one of the six course redesign models. While scaling was the last stage of the process, the cycle was continuous, in which new insights were used to improve upon the effectiveness of any one of the six redesign models. Some of these participating entities that exemplified the utilization of the NCAT methodology were Arizona Board of Regents, The Mississippi Institutions of Higher Learning, Missouri Public Four-Year Universities, State University of New York, Tennessee Board of Regents, and University System of Maryland (What We Do, 2005).

The Redesign Programs

Programs in course redesign (PCR). PCR (NCAT; 1999 – 2004) was the first initiative designed by Carol Twigg and included 30 colleges and universities throughout the US. The project was initially developed to be used as a resource to demonstrate how to redesign quality college courses using technology at low costs. There were six common characteristics shared by each participating institution that encompassed the design model. *Whole course redesign* was preferred for the purpose of making efficient use of faculty time, to reduce cost, and increase course stability. The design supported *active student engagement* to improve student learning outcomes that incorporated *computer-based learning resources* to improve the quality of the learning experience. Students were given more flexibility in how they interacted with the course where student success was measured through *mastery learning* of specific learning objectives. *On-demand help* was included to provide students with needed support to help them establish a connection with the learning environment, which included trained *alternative staff* as a cost saving measure. The success of PCR laid the groundwork for the other initiatives that followed and the development of the six course redesign models that are currently in use to date. Twigg (2003) indicated that the differences between the models "lies on the continuum from fully face-to-face to fully online interactions with students" (p. 30).

The roadmap to redesign. Roadmap to redesign (NCAT; 2003 – 2006) was a U.S. Department of Education funded initiative. The project was designed to develop a more efficient approach to implementing course redesign. The focus was to further "streamline" the developments from PCR and come up with a methodology that could be easily adopted by other institutions; essentially building on progress from PCR. The project paired experienced institutions with other less experienced ones in which they focused on redesigning introductory psychology, precalculus mathematics, Spanish, and statistics courses at 12 colleges and universities.

Increasing success for underserved students. Increasing Success for Underserved Students (NCAT; 2004 – 2005) was a project funded by the *Lumina Foundation for Education*. The project included 24 of the 30 institutions that participated in the first initiative PCR that showed a significant difference in learning outcomes. The goal of this project was to focus on identifying those methods from PCR that were deemed effective at increasing student success rates among the population of underserved students: low-income, African American, Hispanic, and adult students represented the population of interest.

Colleagues committed to redesign. This program initiative (NCAT; 2006 – 2010) was a NCAT funded project as well with support from *Fund for the Improvement of Post- Secondary Education*. The project focused on improving instructional designs using technology at reduced costs. There were 28 participating institutions that were interested in redesigning a range of large-enrollment introductory courses. The redesign efforts included all six redesign models. There were 12 different disciplines that included STEM and Liberal Arts courses. According to NCAT, efforts had reproduced a redesign methodology that was sustainable and cost effective over 10 years of replicating the models.

The redesign alliance. The Redesign Alliance (NCAT; 2006 – 2012) was formed to advance the mission of course redesign to expand to all higher education entities. The objective was to provide a means for institutions and organizations to come together and collaborate on ways to sustain course redesign efforts. The Redesign Alliance provided a platform for the higher education community and others to share ideas about ways to continue to improve learning and reduce cost. The Redesign Alliance was an active membership organization for six years with 86 listed institutional members and 14 corporate members.

State and system course redesign. The State and System Course Redesign (NCAT; 2006 – 2012) was an initiative started by NCAT to work with state-based educational systems interested in large-scale redesign efforts. Over a span of six years NCAT worked with six different state-based educational systems on redesign projects (Arizona Board of Regents, The

Mississippi Institutions of Higher Learning, Missouri Public Four-Year Universities, State University of New York, Tennessee Board of Regents, and University System of Maryland) and three state-based educational systems on redesign pilots (Minnesota State Colleges and Universities, Ohio Learning Network, and University of Hawaii System). The implementation of this initiative was carried out in three phases: building awareness and commitment; campus planning; and implementation, capacity building, and scaling. The purpose of the three-phrased approach was to ensure initial readiness that led to a successful and sustained transition.

Changing the equation (CTE). CTE (NCAT; 2009 – 2012) was an initiative designed to address the issues of high failure rates of students taking LSM courses. CTE was funded by the Bill and Melinda Gates Foundation that focused on redesigning entire LSM courses and programs at the community college level. There were 20 participating institutions (see Appendix F) that successfully redesigned their courses or programs using a fully implemented E-Model design. The current research study focuses specifically on this population of students and seeks to learning more about the students' perceptions of learning mathematics in an E-Model environment.

The Six Course Redesign Models

The six redesign models (*supplemental*, *replacement*, *emporium*, *buffet*, *fully-online* and *linked workshop*) were a result of 13 years of implementing seven program initiatives that started in 1999. During this time, the models were replicated and found to be effective at improving student performance and reducing costs (A Summary of NCAT, 2005). The sustainability of the programs was maintained for as long as the institutions were willing to implement and support specific requirements defined by a particular redesign model. The six course redesign models discovered through the NCAT initiatives can be used to describe nearly all the educational programs or courses that incorporates the use of technology today where learning takes place within and beyond the TI approach to strictly online (Twigg, 2003). The current research focuses on the effective use of the E-Model design in LSM courses or programs across the U.S.

Supplemental model. The supplemental model was a model that most resembled the Traditional Instructional (TI) approach of all the six models. The model remained for the most part instructor centered, which included a lecture component with added supplementary "technology-based, out-of-class activities" (Twigg, 2000). There was a total of 22 institutions that implemented the supplemental model during the PCR program initiative (The Supplemental Model; n.d.). Institutions such as the University of New Mexico and Carnegie Mellon University initially implemented the supplemental model during the PCR initiative. General psychology courses were redesigned at the University of New Mexico, which diminished lectures to one per week and the introductory statistics courses at Carnegie Mellon, which were redesigned to include two lectures per week and one computer lab that provided hand-on experience using statistical software to analyze data. On the other hand, institutions such as the University of Massachusetts-Amherst and the University of Colorado-Boulder implemented redesign supplemental models that altered the number of meeting times and instructional approach in the learning environment (Twigg, 2003). The goal was to make the learning experience of students more active and engaging. The University of Massachusetts redesigned their introductory biology courses by incorporating the use of an interactive learning technology (ClassTallk), while the University of Colorado redesigned their introductory astronomy course. Courses met twice per week, which included brief lectures both in and out of class activities that focused on "teaching students to develop their understanding of the scientific process" (Twigg, 2003, p. 4). Overall the goal of the supplemental model was to supplement the TI approach with opportunities to actively engage students in large classroom lecture environments (Twigg, 2000).

Replacement model. The difference between the supplemental model and the replacement model was a "reduction in class-meeting times" and replacing both in and out of class activities with online assessments using technology (Twigg, 2003). There were 81 course redesign replacement models implemented using two versions of the replacement model (The Replacement Model; n.d.). Pennsylvania State University (Penn State) and the University of Wisconsin Madison implemented the initial the replacement model in the PCR initiative. Penn State redesigned the introductory statistics course by reducing lecture time from three hours to once a week and adding two "computer-studio labs" where students engaged collaboratively or individually on activities.

Similarly, the University of Wisconsin redesigned the general chemistry course, in which a lecture and discussion sessions were replaced with enhanced activities from the internet. In contrast, the University of Tennessee Knoxville redesigned the introductory Spanish course by replacing one of three face-to-face meetings with online interactive software that focused on skill building (grammar, vocabulary, and listening exercises) while the instruction of the other two in-class hours shifted from instructor-centered to student-centered by incorporating more opportunities to engage collaboratively on speaking Spanish and with an emphasis on being culturally aware (Program in Course Redesign-PCR; n.d.).

According to Twigg (2000) the replacement model should not be mistaken for *blended* or *hybrid* models. These models maintained a significant portion of the face-to-face lecture style approaches, while the replacement model replaces much of the traditional lecture approach with in-class and out of class online assessments geared to increase in-class student engagement.

"The key differentiator is that the replacement model *replaces* in-class time with technology-based activities rather than simply *adding* technology-based activities to the traditional course" (Twigg, 2000).

Emporium model (E-Model). The implementation of the E-Model required complete replacement of the TI approach with a computer learning environment using a CLS or instructional software (How to Redesign, 2013; Twigg, 2011). There was a total of 60 E-Model redesign programs that were implemented during the PCR and CTE initiatives (The Emporium Model; n.d.). The development of the E-Model design was modeled by the *Math Emporium* originally developed at Virginia Tech during their initial redesign efforts of a linear algebra course in fall 1997 (Mill, 2005). However, Virginia Tech (among other institutions) participated in the initial program initiative PCR (Twigg, 2003). The Math Emporium was an open lab that consisted of 500-workstations where students had the flexibility to report and complete their coursework with non-mandatory attendance. Unlike Virginia Tech's open lab policy, the University of Alabama redesigned an intermediate algebra course where mandatory attendance was required to attend the *Mathematics Technology Learning Center* (Twigg, 2003). The University of Alabama was one of the 22 institutions that initially participated in the PCR program initiative and implemented a version of the E-Model similar to Virginia Tech's Math Emporium. Years later, as a result of the CTE program initiative, three different versions of the E-Model emerged. These were: *Fixed*, *Flexible*, and *Fixed/Flexible* models (Changing the Equation, 2012.; How to Redesign, 2013). While the E-Model replaced the traditional lecture approach, it relied to a greater extent on a CLS and internet-based activities and assessments with on-demand and personalized assistance as emblems of the E-Model (Twigg, 2011).

Buffet model. The purpose of the buffet model was to truly individualize the learning experience for student by learning more about her/his learning style or unique mode of learning (Twigg, 2003). The buffet approach to learning accounted for several unique factors of each student to tailor a plan that accommodated her/his needs, which (in some cases) included the use of personality type instruments (e.g. Myers-Briggs Type Indicator – see The Buffet Model, n.d.). According to Twigg (2003), these factors included, students' learning preferences, background information, aspirational goals, and various "interchangeable" learning pathways. Ohio State University (OSU) developed the buffet approach following a previously implemented redesign model; the buffet model was developed during the initial PCR program initiative (The Buffet Model, n.d.) The model included multiple learning techniques that students could choose from to learn course objectives.

Twigg (2003) indicated the following regarding OSU's learning options:

> OSU's buffet of learning opportunities includes lectures, individual discovery laboratories (in-class and Web-based), team/group discovery laboratories, individual and group review (both live and remote), small-group study sessions, videos, remedial/prerequisite/procedure training modules, contacts for study groups, oral and written presentations, active large-group problem-solving, homework assignments (graduate teaching assistance graded or self-graded), and individual and group projects. (p. 36)

Linked workshop model. Prior discussions in the current research study expound on the growing concerns of high failure rates in LSM courses or programs across the country (Baily, 2009; Cho & Heron, 2015) and the negative effects this misfortune had on students' performance (Kargar, Tarmizi, & Bayat, 2010; Spradlin, 2009). The goal was to develop workshops that were linked to select college-level mathematics courses that would provide just-in-time support to succeed in the college-level course. The model was discovered by Austin Peay State University during the State and System Course Redesign program initiative, which two developmental mathematics courses were redesigned (The Linked Workshop, n.d.; Twigg, 2003). The model was based on the *Structured Learning Assistance* model developed at Ferris State University in Big Rapids Michigan (History of Structured; n.d.). According to the college's website, the Structured Learning Assistance model was designed to identify "high-risk for failure courses, not students." Austin Peay State University developed the model by totally eliminating the elementary algebra and intermediate algebra LSM sequence courses by providing "just-in-time supplemental academic support to core college-level courses" (Twigg, 2003). This idea of eliminating LSM courses and redesigning college-entry level courses to provide supplemental support to students is currently known as "co-requisite remediation" (Schak et al., 2017). According to Schak et al (2017) co-requisite college-level courses are becoming the new norm in developmental education redesign. In 2015, the co-requisite remediation was implemented by the Tennessee board of Regents for specific introductory college-level courses (Belfield, Jenkins, & Lahr, 2016).

Fully online model. During the implementation of NCATs program initiatives, there were 12 redesign projects that involved various introductory Humanities, Social Sciences, and STEM courses using the fully online model (The Fully Online, n.d.). The fully online model required that the redesign of these courses completely eliminate all face-to-face interactions by moving instruction entirely online, which incorporated elements of the other redesign models: E-Model, replacement, and supplemental (Twigg, 2003). The essentials of the fully online model included web-based resources, the use of a CLS capable of provided immediate feedback and evaluation of both formative and summative assessments, and the use of "alternative staff" or assistants (Twigg, 2003).

According to Twigg (2003), Rio Salado College was one of the participating institutions that best illustrated the use of the Fully Online Model. The project involved redesigning four introductory mathematics courses ranging from pre-algebra to college algebra (The Fully Online, n.d.). These courses were previously taught in a distance learning environment that included the use of a CLS (Academic Systems). The interactive software was used to deliver course content. However, before redesign, the interactive software was used as a supplement to the courses that were delivered online; that mode of instruction was similar to the TI "labor intensive" model where the instructor would be responsible for all aspects of the online learning environment (Twigg, 2003). This type of delivery approach was not cost effective nor made efficient use of the instructor's time to maximize the learning potential of a large group of students.

The fully online model adopted by the college used capabilities of the CLS to deliver course content, provide immediate feedback through "automated grading" of both formative and summative assessments, and the addition of a hired assistant to provide non-academic support to students. This approach allowed the college to increase the number of students being taught by an instructor to 100 students who would be concurrently enrolled in any one of the four redesigned courses rather than offering multiple sections of 35 students per section of each of the four courses. According to Twigg (2003), Rio Salado improved completion rates by 6% and increased the ratio of students per instructor.

Components of the Emporium Model

The "innovation" and success of the E-Model approach was realized in stages that consisted of the *experimental*, *modification*, *replication*, and *expansion* stages (Twigg, 20011).

Since the development of the Math Emporium at Virginia Tech, the modified E-Model was replicated by institutions of higher learning across the country (Changing the Equation, 2012). The development of the E-Model was based on the idea that students learned mathematics through engagement in the learning process (How to Redesign, 2013, Twigg, 2011).

The development of the E-Model at Virginia Tech was the most prominent of all the redesign efforts during the experimental stage that took place during the PCR initiative (Twigg, 2011). Following the PCR initiative, the modification of the E-Model was completed at two universities (the University of Alabama and the University of Idaho) with “underserved” populations in which pre-college level courses were redesigned (NCAT, 2005). The modifications consisted of requiring mandatory attendance, adding one weekly fixed meeting time, using a “commercial software” and creating smaller computer labs different from the large 500-workstation open lab created at Virginia Tech. The success during this stage led to other national program initiatives discussed previously, in which the E-Model was successfully replicated during the Roadmap to Redesign program initiative and then expanded to include State-wide course redesigns during the State and System Course Redesign program initiative (Twigg, 2011).

The popularity of the E-Model grew from the CTE program initiative, in which 38 institutions participated in the course redesign project, but only 20 had successfully implemented the entire course redesign of the E-Model (see Appendix F; How to Redesign, 2013). Some E-Models were designed to include a one-hour face-to-face meeting in a classroom once a week to reinforce concepts for review or to meet and discuss progress as well as any other concerns students had. For the most part, course delivery of instruction was in a computer learning space where students used a CLS to complete their individualized mathematics curriculum (Twigg, 2001; Twigg, 2011). The success of the E-Model depended on the implementation of 10 essential elements (How to Redesign, 2013).

These elements resulted primarily from the first program initiative, PCR, and was later streamlined through the four-stage process, which help define NCAT's methodology (How to Redesign, 2013). These essential elements could be divided into two categories: those that consisted of the Core Structural Elements (CSEs) of the redesign model and the Strategic Operational Elements (SOEs) of the model. These two components described the foundational aspects of the E-Model and the activities that took place in the E-Model learning environment to support active-student engagement where discourse between the student and instructor or tutor was maximized. Simply developing a computer lab or computer classroom and incorporating a CLS did not constitute an E-Model course redesign. Successful implementation of the E-Model design depended on the intertwining of all essential elements and not a select few (How to Redesign, 2013). The following are a list of the 10 essential elements of the E-Model.

Core Structural Elements

- Redesign whole course learning environments.
- Modularize the course content.
- Require mastery learning.
- Measure learning outcomes, completion rates, and cost efficiency.
- Computerize all learning environments using a CLS.

Strategic Operational Elements

- Ensure active student engagement.
- Provide ongoing assessment with computerized feedback.

- Provide one-on-one access to trained professionals to accommodate the individual needs of students.
- Ensure the availability of adequate time on tasks.
- Monitor student success and provide needed assistance.

According to Twigg (2011), two versions of the E-Model were first implemented during the *State and System Course Redesign* initiative. One model was discovered at Jackson State Community College (JSCC), while the other at Cleveland State Community College (CSCC). These were two community colleges in the State of Tennessee. The following discussion of the CSE's and SOE's will be carried out by discussing the implementation of the E-Models at both JSCC and CSCC since all community colleges that participated in the CTE course redesign initiative modeled LSM courses by replicating the E-Model approach discovered at those two community colleges.

Core Structural Elements

Redesign whole course learning environments. In order to maintain the sustainability of the redesign environments, all courses of the same type must be redesigned (Twigg, 2015). According to Twigg (2005), whole course redesigns became a shared responsibility amongst all members of the mathematics department at respective institutions for the purpose of maximizing course efficiency through delivery of content, preparation, and course evaluation. Often innovativeness in course redesign or restructuring was carried out by individual faculty members and was rarely extended beyond the individual instructors' courses due to a lack of departmental or administrative support (Twigg, 2011). When there was a commitment amongst all members of the department to participate in whole course redesign efforts, it reduced the likelihood of "course drift" – the tendency of the instructor to implement instruction suitable for them rather than follow "agreed-upon" learning objectives set by the department as a whole (Twigg, 2015). When the focus of course redesign was the whole course, students benefited academically, and the efficiency of instructional implementation was maximized.

Modularize the course content. Modularization was a course structural design introduced at both JSCC and CSCC (Twigg, 2011). The design was used to replace the three-course sequence of developmental mathematics courses that took three semesters to complete. The three courses were divided into 12 modules at JSCC and 32-mini modules at CSCC that addressed State core competencies. Modularizing the course materials provided several advantages for students. These were: 1) Students only learned skills they needed to be successful in college-entry level mathematics course(s). 2) Students were allowed multiple exits and starting points. 3) Students had more control over the pace of learning. 4) Students only completed what they were not able to complete from the previous semester in the semester that followed. They only completed unfinished modules or ones not attempted. 5) Students had tailored individualized course curriculum to complete (depended on the type of CLS used). And, 6) Students could accelerate and complete the modules in one semester (Twigg, 2011).

Require mastery learning. The idea of mastery learning was that "all students" could reach the same level of mastery of mathematical skills as long as the implementation approach afforded students the opportunity to achieve a certain level of mastery (Groen, 2015). According to Groen (2015), criterion-referenced exams with a set mastery level (i.e., between 70% to 80% mastery) were incorporated into the learning experience with "well-defined," specific, and achievable learning outcomes throughout the implementation process. The essential elements (i.e., the CSE's and SOE's) of the E-Model course redesign were uniquely suitable for including mastery learning as an instructional tool.

During the State and System Course Redesign initiative both JSCC and CSCC used mastery learning as an assessment strategy in the redesigning of LSM courses using the E-Model redesign approach. The efforts of the institutions saw an increase in learning outcomes and success rates at lower costs (Twigg, 2011). The E-Models used by these institutions were replicated in the CTE program initiative where more results favored the successful inclusion of mastery learning as an effective pedagogical tool (How to Redesign, 2013). The potential for using mastery learning as a tool to aid in improved student performance and achievement had since been met with both mixed and promising results of the effectiveness of the approach (Bradley, 2016; Groen et al. 2015; Guskey, 2007).

Measure learning outcomes, completion rates, and cost efficiency. An essential component of the *Four Step Process* was proof-of-concept (What We Do, 2005). In order to assess the effectiveness of the E-Model course redesign, it was important to collect data supported by strong evidence-based results. The success of the NCAT methodology depended on the measurement of these data-driven results. These results came in the form of comparison analyses of assessment data (i.e., pre- and post-test results and course exams) between students taught using the TI approach versus those taught using the E-Model approach to assess the extent of learning and rate of completion. Improvements in the quality of learning at low costs were demonstrated through cost analyses (Twigg, 2015). According to Twigg (2011) both JSCC and CSCC improved overall student success rates. There was a 44% increase in grades of C or better at JSCC and an increase of approximately 31% at CSCC. In addition, there was a 20% reduction in cost at both community colleges.

Computerize all learning environments using a CLS. To understand and appreciate the crucial role of technology use in advancing the mission of NCAT, it was important to discuss related literature that focused on the use of specific types of technology that were used to enhance student learning. This discussion dates back nearly six decades, envisioned by educators during a time when computers were being used in "personnel trainings" in the late 1950's (Kulik, Kulik & Cohen, 1980). Support for the inclusion of technology in education gain momentum in 1965 when different governmental agencies (private and public) along with other foundations began initiating funding initiatives to support the incorporation of technology in education (Kulik et al., 1980). Kulik et al. (1980) conducted a meta-analysis of the use of *Computerized-Assisted Instruction* in education that included 59 evaluations of college teaching using technology across curricular spectrums that found small but significant findings, which indicated the potential for increased student performance when incorporating the use of technology to assist instruction.

Since then, the 1980s and 90s saw an influx of research supporting the use of the CLS instructional technology as tools to supplement traditional classroom instruction to enhance the lesson and improve student learning outcomes in general. This trend was more evident in mathematics education research (Bialo & Sivin-Kachala, 1996; Dalton & Hannafin, 1988; Fitzgerald & Koury, 1996; Ford & Klicka, 1998; Kulik & Kulik, 1991). It was important to note that the use of technology during this span of time focused on technology use as a supplemental tool to the TI approach. Interestingly, it was particularly towards the end of the 20th Century that a focus on completely overhauling courses and programs became an important trend initiated through NCAT program projects, which used technology as a critical component in course redesign to improve student performance at reduced costs (Twigg, 2003).

Implementation of the E-Model course redesign involved more than just the inclusion of a technology component or CLS. Advancements in technology over the past couple of decades, along with its incorporation in education, had sparked many innovative and alternative options for enhancing students' learning experience in traditional and non-traditional learning environments. Particularly, in the E-Model course redesign, the CLS provided opportunities for "ongoing assessment" and computer-generated feedback (Twigg, 2015). The inclusion of a CLS (i.e. adaptive or interactive mathematics software) in the E-Model course redesign, enhanced the teaching of course content in mathematics and the learning experience of students (Twigg, 2011). According to Twigg (2015), computerizing all leaning experiences provided the benefit of continuous evaluation and "automated" feedback on homework and other assessments (e.g., low-stakes quizzes). The E-Model redesign approach made it suitable to provide this type of assessment. Both JSCC and CSCC used the *MyMathLab* software (CLS) to deliver student instructional content (TBR: Developmental, 2009).

Strategic Operational Elements

Ensure active student engagement. According to Twigg (2011) students learned math by being active participants in the learning environment. Learning environments that were more instructor-centered delivered course content in lecture form. Students in these types of learning environments were more passive than active during the learning experience. Replacing all lectures with engaging student activities and tasks modeled a student-centered learning environment, which was central to the E-Model course redesign (Twigg, 2003). According to Twigg (2015) computerized learning environments should be structured to promote student interactions amongst one another. A suggested alternative to a lecture-based learning environment was to create opportunities for students to collaborate on assignments in small groups within the learning environment or online.

Both JSCC and CSCC implemented their redesign projects in different ways. Two versions emerged. These were the fixed and fixed/flexible versions (Twigg, 2011). The fixed version was introduced at JSCC where students were required to meet three scheduled hours in the SMART Math Center (computer lab) with their instructors to receive one-on-one assistance (TBR: Developmental, 2009). In contrast, students at CSCC were allowed flexibility in completing their required hours. Students completed one hour each week in a computer learning space with an assigned instructor and were allowed the flexibility to complete the other two hours in the open computer lab each week (TBR: Developmental, 2009).

Provide ongoing assessments with computerized feedback. Learning of any course content takes time and effort to yield a desired outcome. Twigg (2015) indicated that learning in general was not a "spectator sport" and that students performed better when instructional methods included various and more frequent formative assessments. Using "computerized-based assessments" was an effective way to provide ongoing evaluation of students' knowledge with "automated" feedback (How to Redesign, 2013). For example, computerized assessments "…includes tutorials, exercises, and low-stakes quizzes that provide frequent practice, feedback, and reinforcement of course concepts" (Twigg, 2013, p. 2).

According to Twigg (2011), students in the modularized E-Model courses at both JSCC and CSCC had similar assessment plans. Assessments included homework, attendance, a notebook grade and "proctored" exams at the end of each module. JSCC divided the original three developmental courses into 12 modules. CSCC divided the three original developmental courses into 32 "mini-modules," in which deadlines were set to have a module completed weekly at CSCC (How to Redesign, 2013). Moreover, homework assignments had to be complete for each module. Students had to earn a minimum of 80% at JSCC and 70% at CSCC on each of the homework assignments to progress on to preparing for the module exam. Before a student could move on to the next module, she/he had to complete the module exam with 75% mastery at JSCC and 70% at CSCC. The remaining percentage of the overall module grade (25% at JSCC and 30% and CSCC) was attributed to a percentage of the homework grade, attendance, and notebook.

Provide one-on-one access to trained professionals. The student-centered learning environment in the computer lab/classroom was staffed with trained support personnel to provide individualized assistance to students when they needed the help (Twigg, 2011). Due to the mode of instruction in the TI environment, students often did not have the opportunity to be actively engaged because instruction was more lecture-based. When students did have the opportunity to be engaged, they were less likely to speak-out because they didn't want it to be known that they didn't understand (Twigg, 2015). Students benefited from the E-Model approach to learning because they had immediate access to faculty members and other trained individuals to provide personalized assistance. With the advancement in interactive software or the CLS, students had access to immediate computerized feedback on homework and other assessments as well.

According to NCAT (TBR: Developmental, 2009), staffing the computer lab with both tutors and faculty worked well. At CSCC, the lab was staffed with faculty members and five trained tutors. Faculty were able to contribute eight to ten hours per week in the computer lab. Faculty were also assigned approximately 10 sections of 18 students, which met once per week in the computer classroom where students received personalized assistance and met with their instructor to discuss their progress. In addition to paid staff, one volunteer worked five to six hours a week. At JSCC, the SMART Math Center was staffed with both faculty and tutors. Students met in the "SMART Math Center" with their instructor three times per week" (i.e., a maximum of 27 or 30 students per section) where students received personalized assistance on course materials. In addition, instructors were able to take attendance and monitor students' progress during this time.

Ensure the availability of adequate time on tasks. The structural design of an E-Model learning environment required that students be actively engaged from the time they entered the computer lab/classroom until the time they exited. This type of design required that students spend the necessary time on tasks outside the lab/classroom settings as well. The key to successful completion of the modularized curriculum was to ensure that methods were in place that motivated students to devote the necessary amount of time on completing tasks (How to Redesign, 2013). According to Twigg (2015), mandatory attendance driven by rewards and punishment was an effective way that motivated students to attend both the computer lab and classroom settings. Students most likely did not attend these learning environments when they were not obligated. However, when students used effective learning strategies and managed their time well, they often put forth the effort and performed better (How to Redesign, 2013).

Regardless of the versions of the E-Model implemented, both JSCC and CSCC required mandatory attendance (Twigg, 2011). Students at CSCC were enrolled in "shell courses" with an assigned instructor. The shell courses were constructed by dividing the 12 modules (formerly three LSM courses) into three different courses each with four modules. These students met in the SMART Math Center with their assigned instructor. In contrast, implementation of the E-Model design was different at JSCC, attendance was mandatory for both learning environments (computer lab/classroom). According to Twigg (2015) between five and ten percent of the final grade was accounted for by attendance. Specifics regarding the redesign efforts for both community colleges can be found on the NCAT website (see Tennessee Board of Regents, 2009).

Monitor student success and provide needed assistance. Central to the E-Model design was the incorporation of a CLS. These interactive or adaptive mathematical software programs supported effective "pedagogical" instruction (Twigg, 2015). Faculty members were able to use the grading tools of the CLS to monitor students' progress (e.g., performance on assigned homework, quizzes, or exams). The tracking capabilities of the CLS allowed instructors to keep track of the amount of time students spent in the CLS. Some of the more advanced adaptive software programs tracked the time students spent working assigned curriculum. Twigg (2015) asserted the following regarding actions that should be taken when students lost interest or motivation to stay the course:

> Requiring attendance and awarding attendance/participation points are essential, but they are only the starting points. Two additional steps need to be taken: First, someone must monitor each student to see who is and who is not meeting the attendance/participation requirement. Second, once those students have been identified, someone must contact them and indicate clearly that they are expected to come to class and do the work. (p. 10)

An advantage of the E-Model course redesign was that it supported efficient instructional practices (Twigg, 2015). For example, instructors at both JSCC and CSCC were able to devote more of their time on "pedagogical and organizational issues rather than on materials creation, adaptation, and maintenance" when computerized software was used (Twigg, 2011). Faculty members at these institutions were able to successfully track the progress of students and intervened when it was necessary.

The E-Model Course Redesign Research

Since the development of NCAT in 1999, redesign efforts of LSM courses have grown exponentially at institutions of higher learning. Researchers have begun to answer the call for more rigorous empirical research studies that explored the impact of LSM course redesigns on student performance nation-wide. The following section is a review of the latest research literature that explored the impact of students' learning experiences in the E-Model course redesign at community colleges across the county beyond the CTE program initiative implemented through NCAT from 2009 – 2012. The first part of the review discusses the results and implementation of several program evaluation studies assessing the E-Model methodology. The proceeding part of the review discusses additional empirical research studies that investigated the impact of learning using the E-Model approach, which focused on students' psychological well-being (affect and motivation) as well as performance.

E-model evaluations. Eckhardt (2016) completed an evaluation at Manchester Community College in New Hampshire during spring semester 2016 to evaluate the effectiveness of the E-Model course redesign. Like many other troubling signs of low completion rates in LSM courses, the institution sought to redesign all LSM courses offered at the college. The redesign of these courses involved implementing the E-Model by using the adaptive learning CLS (ALEKS), in which the pedagogical nature of the course was rooted in Bloom's theory of mastery learning (Guskey, 2007). The evaluation project focused on measuring students' desire to persist through and succeed in the E-Model course redesign by understanding more about the impact of the E-Model design on students' achievement, growth mindset (the belief that one has boundless potential to improve) and positive affect dispositions (Eckhardt, 2016).

The evaluation project was a mixed method quasi-experimental design. The researcher analyzed dated collected from both faculty and student interviews and focus groups. Collection of data also included an open-ended faculty questionnaire and students' responses on an end of course Likert scale questionnaire. Analysis was performed on data collected from two redesigned courses (Fundamental Math and Pre-Algebra). The overall results supported evidence that the E-Model course redesign was a success. A Two-Sample *t*-test on combined data from the two courses when compared to the TI approach was significant ($z = 4.45$, $p < .0001$). The odds of success in the E-Model courses was 2.47 times as likely as those students in the TI courses. The effect size was measured by the computation of the Absolute Risk Difference, which indicated the E-Model increased the chances of a student passing the course by 19%. The researchers also found that students exhibited higher levels of both positive affect (89%) and growth mindset (95%).

Krupa et al. (2015) completed an evaluation study that determined impact on students' achievement and their responses to open-ended mathematical problems that assessed students' conceptual understanding in contextual situations. While the researchers recognized the fact that the E-Model methodology did impact student learning and achievement, they questioned whether this impact improved students' ability to apply mathematical concept in contextual situations as well as gain a conceptual understanding of mathematical conceptual. The evaluation consisted of a quasi-experimental matched comparison design. The researchers compared the performance of students taught using the E-Model design to students taught using the TI approach. They assessed students' conceptual understanding by using three contextual problems (the burger, ticket, and chocolate mixture problems).

The researchers discovered that students who took the E-Model course scored significantly higher on end-of-course exams (μ = 70.75, σ = 15.29) than those who were taught using the TI approach (μ = 65.49, σ =13.12). They also found that these students using the TI approach were more likely to be better at interpretation of the meaning of equations in context than students taught using the E-Model. Interestingly, both groups were not able to express their mathematical reasoning in contextual situations. Extended research found that students taught in the E-Model environment who had high Scholastic Aptitude Test (SAT) math scores performed better in the E-Model course than those with low SAT math scores who did well in the TI approach.

More recently, a study completed by Webel, Krupa, & McManus (2017) came to a similar conclusion that students were able to reapply procedural knowledge but had limited ability to use symbolic language to solve application problems in contextual situations. Notably, there has been wide-spread debate regarding whether the learning of mathematical concepts should focus more on the development of "procedural knowledge" or rooted in developing students' "conceptual knowledge" (see, Baroody, Feil, & Johnson, 2007). Nonetheless, it is left up to the individual institution to implement "design decisions in the context of the constraints it faces" (Twigg, 2011, p. 26). While there will be variations in the implementation of the SOEs, the CSEs should be included in all E-Model designs.

Vallade (2013) completed an evaluation of three rural community colleges that redesigned their LSM courses using the E-Model methodology. Empirical evidence was analyzed using a causal-comparative research design that included additional analyses to answer two research questions. The goal of the study was to investigate the effectiveness of the E-

Model design by comparing completion rate data and mean differences between students taught using the E-Model design to those taught using the TI approach.

The results were aligned with the majority of research that attested to the effectiveness of the E-Model design. While results were statistically significant when comparing the completion rates and mean differences between the E-Model design and the TI approach (with a reported effect-size (eta squared) value of 0.10 for the mean difference), more notable were the comparison of the results between the two models for the same students who enrolled in their college-level mathematics course (College Algebra) after completing the LSM courses. The chi-square analysis revealed that a statistically significant result, $\chi^2(2, N = 4465) = 25.32$, $p < .001$ existed between the two methodologies. Follow-up tests were not performed to determine where the differences were in regard to the pass, fail, and withdrawal rates. However, the pass rate for the E-Model was 74.3%, $n = 1{,}043$ and the pass rate for the TI approach was 67.0%, $n = 2{,}050$. Additionally, results were found to be statistically significant, $t(3658) = -12.91$, $p < .001$, when comparing the mean differences between the E-Model design ($\mu = 2.69$, $\sigma = 1.31$) with $n = 1{,}203$ and the TI approach ($\mu = 2.10$, $\sigma = 1.27$) with $n = 2{,}457$. Reported effect-size (eta squared) was 0.44.

Patson (2014) completed an evaluation study at Delaware Tech Community College. The design of the study was a quasi-experimental mixed-methods survey design. The aim of the evaluation research was to measure the effectiveness of the E-Model courses and document features of the E-Model methodology that both supported and hindered student learning. The college redesigned two LSM courses (Math 012 and Math 015) during the fall 2012 and Spring 2013 academic year.

Different from the outcomes of previous studies, the researcher found a significant decrease in the performance of students taught using the E-Model design for both LSM courses for consecutive semesters when compared to students taught using the TI approach. Students' performance in Math 012 decreased by 29% in Fall 2012 and 9.5% in Spring 2013. There was a decrease in student performance by 41% in Fall 2012 and 7.7% in Spring 2013 for Math 015. Additional testing found no significant differences when comparing these groups of students in their college-level mathematics course (Math for Behavior Sciences). Although the results were not significant, the percentage of failures decreased in the following semester.

Patson (2014) also completed an extensive investigation that included detailed analysis of the E-Model methodology that she indicated was lacking in other similar type evaluations. Through qualitative analysis, she found that the top features that supported student learning were the CLS (*MyLabPlus* with 29.8% – a Pearson product similar to *MyMathLab*), the "Math Success Center" (26.3%), with "mastery learning" and "getting points" (both 15.8%) for n = 57. In contrast, the top features that hindered learning were the "amount of time course required" (17.2%), the "Math Success Center" (15.5%), and "None" (13.8%) for n = 58.

While these evaluations answered the call for more rigorous empirical studies (Bonham & Boylan, 2012; Hodora, 2011), few fell short of providing a holistic assessment of the learning experiences of students. A more holistic assessment includes learning more about students' psychological well-being in addition to investigating empirical data on completion rates, achievement, and cost effectiveness. A holistic assessment is even more critical given that students taught using the E-Model methodology were learning in an environment that was vastly different from the TI approach and a methodological design geared towards the autonomous or self-determined learner. Being able to assess whether students' basic psychological needs were met, provides additional insight into the interpretation of results regarding the effectiveness of the E-Model methodology. For example, Patson (2014) indicated that a possible reason the E-Model was not found to produce significant improvements in student learning could be due to the fact that the evaluation study was completed during the first implementation of the E-Model. Although the results were not significant in any case, the researcher's explanation on the impact of the instructional features used (i.e., the SOEs) and investigation of students who withdrew from the course or stopped attending, could add additional interpretation. Moreover, interpretation of the results revealed that it was a lack of student engagement to complete tasks (e.g., going to the computer lab, working in the CLS, or completing assignments etc.) that contributed to the possible reasons for the low performance. What was needed and not explored was an assessment of the psychological ramifications of learning mathematics in the E-Model learning environment. Of these studies, only the evaluation study produced by Eckhart (2015) provided a more holistic investigation of the impact of students' learning using the E-Model, which included an assessment of students' ability to persist through to the end of the course, their growth rather than fixed mindset (synonymous to a self-determined student who parades higher levels of competence as defined in SDT; Ryan & Deci, 2017), and attitudinal perceptions. Each study contributed to the flourishment of research on using the E-Model methodology in unique ways. Insights gained from each of these evaluations could be used as a resource for the LSM community at large, which includes administrators, faculty, and other interested stakeholders to aid in the decision-making process regarding changes in implementation of the E-Model methodology for sustainability purposes.

A measure of psychological constructs and performance. Notably, none of the prior studies discussed nor the ones that will be introduced in this section used randomization (a rare design option in educational research and evaluations due to cost, logistical, political, or ethical constraints; Bamberger, Rugh, & Mabry, 2012), which eliminated the generalizability of results. Another area of interests that could potentially provide an alternative form of generalizability was exploring the psychological nature experienced by students through survey development, design, and validation (DeVellis, 2012); relative to learning mathematics using the E-Model methodology. As previously discussed, the state of students' psychological health was an area that needed to be explored (Bonham & Boylan, 2012) and should be included in the evaluation for measuring the impact of a learning environment vastly different from the TI approach (Liaw, 2012; Mireles, 2012). Assessing students affect and motivational dispositions can strengthen the research design and provide additional interpretation to support the triangulation of non-randomized quasi-experimental results (Bamberger, Rugh, & Mabry, 2012).

Williams (2016) indicated that the E-Model methodology was the best instructional approach designed to provide developmental mathematics learners the necessary skills to succeed by helping them to become self-regulators of their own learning needs. This ability to take more ownership of one's learning experiences was a necessary skill that benefited students not only academically but promoted life-long learning (Chow & Chapman, 2017); and "…more effective self-functioning, resilience, and enduring psychological health for the long term" (Ryan & Deci, 2017, p. 12). This view was aligned with an evidenced-based recommendation by the U.S. Department of Education: which was, "Teach students how to become self-regulated learners" (Schak et al., 2017). Self-regulation will be a construct explored in the current research study and discussed in a later section.

In order for students to achieve and maintain an increased level of personal independence and self-regulation that supports positive learning experiences, one question comes to mind.

Were the learning experiences of students "satisfying" their basic psychological need to attain autonomy, competency, and relatedness in the E-Model learning environment, which was designed for the autonomous or self-determined learner? Additional review of the research literature focused attention on the investigation of the psychological health of LSM students and how their affect and motivational dispositions impacted student learning and achievement when using the E-Model methodology as an instructional approach. The current section will shed light on this impact by examining various psychological factors to assess the impact of students' Basic Psychological Need Satisfaction (BPNS) and use of self-regulated learning strategies as building blocks of students' learning potential.

Perceived self-efficacy was defined as a psychological construct that had emerged as a significant predictor of students' motivation and performance (Komarraju & Nadler, 2013). According to Zimmerman (2000) self-efficacy was a "personal judgement" of one's own belief regarding their ability to achieve a goal or complete a task. Confident students tended to perform better and were more self-determined (Komarraju & Nadler, 2013). This level of perceived self-efficacy was synonymous to a student with increased autonomy.

Hendricks (2012) completed a study that determined whether mathematics self-efficacy and technology self-efficacy were predictors of mathematics achievement when considering three different instructional approaches (online, hybrid, and traditional) for developmental mathematics courses. Logistics regression results revealed that only mathematics self-efficacy was a significant predictor of students' success on completing the end of course exam χ_2 (2, N = 130) = 6.54, p = .038. Given that mathematics self-efficacy was the only predictor of student success. Regression analysis indicated that only mathematics self-efficacy statistically predicted students' success in the Hybrid version, F (1, 44) = 6.155, p = .017. Particularly, the Hybrid version was setup similar to the E-Model but included a learning environment that mirrored the TI approach.

Mathematics anxiety was another construct of study. Simply put, it was defined as the fear of working in mathematical situations that could hinder students' ability to perform (Iossi, 2007). Kargar (2010) found that mathematics anxiety negatively impacted students' mathematical thinking and attitude. In a study completed by Williams (2016), results indicated that students exhibited more levels of fear when they were taught in a learning environment that was more different than the TI approach. The researcher carried out a causal-comparative research study designed to assess the impact of the different learning environments (E-Model vs. TI) on students' math anxiety and readiness to succeed in College Algebra. The researcher collected pre/post data from the administration of both the "Abbreviated Mathematics Anxiety Scale (A-MARS)" and the "Algebra Readiness Test" (an end-of-course exam developed by mathematics faculty at the participating community college). Data were collected from students in an intermediate algebra course. Mixed-Methods Repeated Measures ANOVA indicated a significant main effect (between subject), $F(1, 57) = 5.773$, $p = .020$, for $\alpha = 0.10$, which indicated that students taught using the TI approach had lower levels of math anxiety than students learning in the E-Model course. There was also a significant interaction effect (time*model type), $F(1, 57) = 4.883$, $p = .031$ for $\alpha = 0.10$, which indicated that math pre/post anxiety results had an effect on the model type. Students in the TI group experienced less anxiety. When examining the readiness of students to take their college-level mathematic course, the Mixed-Methods Repeated Measures ANOVA results had the opposite effect. There was only a significant main effect for time (within subjects), $F(1, 57) = 30.151$, $p < .01$, which indicated a significant difference in the achievement over time with respects to the models (E-Model vs. TI approach).

Another interesting study completed by Pachlhofer (2017) focused on the psychological nature of student learning. The researcher wanted to identify motivational factors that had an impact on students' success completing their LSM courses at three different 2-year colleges that modularized their LSM courses using the E-Model methodology. The researcher also wanted to determine which of the motivational factors were significant predictors of students' success as well as determine whether the motivational factors (separate dependent variables) were influenced by differences between the institutional types (i.e., the three different colleges as independent variables). The researcher used only the motivational subscales of the *Motivated Strategies for Learning Questionnaire* (MSLQ) to complete the study. The MSLQ was designed to improve teaching and learning postsecondary, which included two types of scales (motivational and learning strategies scales; Pintrich, 1987). The constructs of interest were "intrinsic and extrinsic goal orientations, task value, control of learning beliefs, self-efficacy for learning and performance".

Pachlhofer (2017) found that students' highest goal orientation was extrinsic in nature (M = 5.5, SD = 1.1). According to Ryan & Deci, 2000 extrinsic motivation can be described on a continuum with four regulatory styles ranging from external regulation to integrated regulation (internal). The items from the MSLQ were more external in nature. The other motivational characteristics were self-efficacy (M = 5.3, SD = 1.2), control of learning beliefs (M = 5.2, SD =1.2), task value (M = 5.1, SD = 1.2), and intrinsic goal orientation (M = 4.9, SD = 1.0). Multiple regression analysis yielded at least one significant result. Both task value (β = -.24) and self-efficacy (β = .31) were predictors of students' success to complete their LSM course work,

$F(5, 183) = 3.46$, $p < .05$, $adj\text{-}R^2 = .061$, significant at $\alpha = .05$. ANOVA results were shown to yield statistically significant differences between the three institutions (I1, I2, and I3 - independent variables) and the impact these variables had on students' motivational characteristic (extrinsic motivation, task value, and self-efficacy - separate dependent variables). Through post hoc analyses, the researcher found that students' extrinsic motivation was significantly higher for I1 than I2 (differ by, 0.48); students' task value was significantly higher for I1 than I2 (differ by, 0.50); and students' self-efficacy was higher for I3 than I2 (differ by, 0.65). Practically, the effect sizes were $\omega^2 = 0.03$, 0.05, and 0.04 respectively (small effect = .01 and medium effect = .06; http://imaging.mrc-cbu.cam.ac.uk/statswiki/FAQ/effectSize).

Surprisingly, fewer research studies explored whether the E-Model methodology had an impact on students' psychological well-being with respects to certain demographic variables (e.g., age, and number of semesters completed). While this was the case, based on the review of literature, a fairly recent and extensive study completed by Chockla (2013) focused on whether students' placement scores and gender were significant predictors of student achievement using the E-Model methodology. The researcher also wanted to identify students who were in jeopardy of failing the end-of-course exam. The study was a pre/post comparison quasi-experimental design that included multiple regression analyses on five different models that compared differences between the E-Model method and the TI approach. Data were collected over the course of three semesters at a rural community college in North Carolina that involved three LSM courses (Math 030, Math 040, and Math 050).

Both Models 1 (Spring 2012) and 3 (combined data Fall 2012 and Spring 2013) had similar designs, which the independent variables were placement scores and gender; predicting the effects of the pre/post-test differences between the two methodologies. However, Model 1 analysis was performed with Math 040 data and Model 3 analysis was performed with Math 030 data. For both Models, students with low placement algebra scores tended to perform slightly better than those with higher placement scores (Model 1 with adj-R^2 = 0.37) and (Model 3 with adj-R^2 = 0.29), both significant at $\alpha = 0.01$. The researcher found that male students were slightly more likely to perform better in Model 1, significant at $\alpha = 0.05$, but gender was not significant in Model 3. The other three models were slightly different in design.

Model 2 (Spring 2012) predictor variables were placement scores and methodology (E-Model vs. TI approach) with the same dependent variables as Models 1 and 3. However, analysis was performed on Math 050 data with a similar outcome as Models 1 and 3 regarding placement algebra scores. The E-Model methodology produced statistically significantly higher student achievement scores than the TI approach with an *adj*-R^2 = 0.23 and α = 0.01 and 0.05 respectively.

The predictor variables for Model 4 (Fall 2012 and Spring 2013) were placement scores, gender, and semester. Analysis was performed with Math 040 data. Similar to the previous results regarding the placement scores, students with low scores benefited more from the E-Model methodology than the TI approach. However, females scored statistically significantly higher than males. Moreover, students who took the E-Model course in Spring 2013 scored statistically significantly higher than those who took it in Fall 2012 with *adj*-R^2 = 0.29 and α = 0.01, 0.05, and 0.05 respectively.

Lastly, the predictor variables in Model 5 (Fall 2012 and Spring 2013) were placement scores, pretest, and semester. The response variable was post-test. Analysis was performed with Math 050 data. The researcher found that certain prior assessment identifiers (i.e., placement scores and pretest) were able to identify that approximately 13% of students would be in jeopardy of failing the post-test when considering other factors related to pre-course implementation with *adj*-R^2 = 0.43 and $\alpha = 0.10$. Regarding the variable semester, students in Fall 2012 scored statistically significantly higher than those in Spring 2013.

Other noteworthy mentions were that none of these studies examined whether the psychological factors were influenced by specific demographic variables (e.g., age and number of semesters attempted or completed a course) relative to the E-Model methodology. More specifically, it would be interesting to find out whether learning in the E-Model environment had an effect on students' BPNS by examining the number of semesters students attempted or completed an E-Model course and age differences in addition to gender. For example, a study completed by Peeler (2016) found that the pass rates of students who had to complete more than one semester of course work had decreased pass rates than students attempting a course for the first time, which this rate persisted through the sequences. The researcher used the Markov Chain model to investigate the pass rates in the sequence of the E-Model courses compared to the sequences of the TI courses at a North Carolina community college. Additional results revealed that male students were less likely to be placed in a lower sequence than female students. When examining racial placement, White students were less likely to be placed in a lower course sequence than Black/African American students. The researcher also found that students who were placed in their college-level mathematics course, as a result of placement indicators different from the traditional college placement exam (e.g. High school GPA), had a lower pass rate but comapriable to those students who were placed as a result of the traditional college placement exam. This finding makes sense given that students who were generally placed in their college-level introductory mathematics courses, who had placement scores slightly above the cutoff value, tended to need additional assistance to help them progress through their college-level course work (Baily, 2009).

According to Bray and Tangney (2017), learning environments that were autonomy-supportive afforded students the chance to build their mathematical confidence and increase their interest in learning the subject by supporting their BPNS. This claim supports assertions made by researchers like Bonham and Boylan (2012) who advocated for empirical research studies that explored the impact on students' psychological health as it related to learning using the E-Model methodology. Prior discussions have shown that researchers have responded to the need to learn more about the impact of students' psychological health as it related to learning in the E-Model environment. Not surprisingly, the latest research in this area had produced mixed results but the outcomes were promising. According to Chen (2016) this had been a consistent pattern (in general) with emerging empirical studies in this area. For example, a study completed by Helming and Schweinle (2014) found that students overall did not experience negative effects on their motivation as they transitioned to the E-Model course redesign. The researchers used a validated survey instrument that measured students' academic self-efficacy (The Patterns of Adaptive Learning Scales developed by Midgley et al., 2000) to assess students' perceptions of their learning experiences. A more recent study completed by Webel, Krupa, and McManus (2017) reported that "students expressed mixed feelings" regarding the impact that the E-Model structural design had on their psychological well-being.

The commonality that continued to exist and seemed to be the driving force of the mixed results amongst these studies appeared to be the implementation of the SOEs. It has been documented that if each of these institutions were truly implementing the 10 essential elements (i.e., the CSEs and SOEs) of the E-Model methodology, as they should be applied, then there should exist a positive effect on students' learning and achievement (Twigg, 2011; How to redesign, 2013). Specifically, for the E-Model methodology, there exist must documentation to support this claim (see Changing the Equation, 2012). In light of the mixed results, a vast majority of the outcomes discussed in the current research study supports initial claims that the E-Model methodology had a statistically significant positive effect on students' learning experiences. However, a true measure of the impact of the E-Model methodology were measured by students' achievement post completing the E-Model courses by measuring students' successful completion of their college-level mathematics course. For example, two of the studies discussed, measured this impact. One found a statistically significant result (Vallade, 2013) supporting the effectiveness of the E-Model methodology and the other did not (Patson, 2014).

Metacognitive self-regulated learning strategies (MC-SRLS). As discussed previously, the implementation of the SOEs should include instructional strategies that allowed students to develop the skills necessary to become self-determined learners. This includes a student-centered learning environment that supported students' BPNS (Black & Deci, 2000). According to Gagne (2003), researchers found environments that supported students' BPNS mediated the relationship between autonomy-supportive environments and positive outcomes. Providing students the means to use and develop MC-SRLS created a pathway to becoming a self-determined learner (Chung, 2005). Putting students on a path to developing more autonomy, can be achieved by incorporating MC-SRLS into the implementation process.

Metacognition can be defined as the process of "thinking about thinking" (Owen & Vista, 2017). Metacognition combined with SRLS represented the action of taking control of ones' own learning through regulation. According to Pintrich (1987), MC-SRLS consisted of three processes: These were: planning, monitoring, and regulating (i.e., evaluating; Schraw, 1998).

Each one of those processes were specific activities that students engaged in as part of the learning process. In general, planning involved choosing appropriate strategies (e.g., setting goals or selecting specific strategies for the task) and allotting resources (e.g., managing time on tasks or seeking help from support personnel) that influence the learning outcome (Schraw, 1998). Monitoring involved specific tasks that helped students assess her/his understanding of the material (Steltenpohl, 2012). For example, engaging in self-inquiry or self-quizzing of course content. Regulating involved the process of evaluating the effectiveness of ones' ability to take control over her/his learning as well as reflecting on whether the chosen strategies were useful (Schraw, 1998). In other words, "appraising the products and efficiency of one's learning" (Schraw, 1998, p. 115). This process was defined as continuous (Pintrich, 1987) or cyclical as a result of reflecting over one's ability to apply SRLS (Steltenpohl, 2012). Additional information regarding the reliability and validity of the MC-SRLS from the MSLQ (Pintrich, 1987) will be discussed in Chapter 3.

Chapter Summary

In summary, the previous review of literature focused on several key components that defined the current research study. The review began with an introduction of SDT (the theoretical framework), which asserted that individuals desired to achieve autonomy, competence, and relatedness in their social environments (Ryan & Deci, 2000; 2017). Given the methodological design of the E-Model, SDT was the best fit for examining the effects of the E-Model methodology on students' psychological well-being. A review of the NCAT methodology was essential because it created the blue-print for the existence of all six redesign models, which were streamlined through the six program initiatives that followed the first program initiative, PCR (Twigg, 2005a; Twigg, 2011).

The current research study specifically focused on the development of the E-Model methodology because it had proven to be a successful redesign method, alternative to the TI approach, for increasing students' learning and performance, in mathematics education in general but more so in LSM education (Changing the Equation, 2012). The success of the E-Model methodology depended on the implementation of the 10 essential elements which could be divided into two types, the CSEs and SOEs. According to Twigg (2011), it was the responsibility of each institution to decide on design implementation of the SOEs given the "constraints" unique to the institution. While the 10 essential elements were common to all implementation efforts of the E-Model, it was the implementation of the SOEs that appeared to influence the mixed, but promising results pointed out in the review.

Beyond the CTE program initiative, researchers began to answer the call made by others such as Baily (2009) for more empirically-based research studies that investigated the E-Model methodology effects on students' learning and performance. The calls made by researchers such as Bonham and Boylan (2012) advocated for more rigorous evidenced-based research investigating the effects of the E-Model on students' psychological health, which were among increasing research studies exploring the influence of the E-Model methodology.

Given the unique structure of the E-Model methodology, more research has been documented attesting to the effectiveness of the design based on earlier works by NCAT (Changing the Equation, 2012) as well as additional studies beyond CTE (e.g., Pachlhofer, 2017; Vallade, 2013). The promising but mixed results of studies like Krupa et al. (2015) and Kargar (2010) still leave more unanswered questions related to the effectiveness of the E-Model methodology. One posing overarching question remains to be answered. To what extent does the E-Model methodology support students' BPNS? The next chapter will discuss the methodological design of the current research study to further address this question.

CHAPTER 3: METHOD

The methodology of the current research study introduced the participants of the target population, the recruitment of these participants, followed by a discussion of the consent form and incentive. The discussion focused on the development of the EMMS, items adopted from other instruments with the inclusion of newly developed items, and procedures for satisfying the validity and reliability of these new items. The researcher discussed procedures specific to item development and general procedures for carrying out the current research design. Discussion included the process of obtaining approval to begin data collection, establishing initial contact with potential participating institutions, and the approach for securing and collecting data. The chapter concluded with a detailed account of planned analyses, the data cleaning process, and analyses to be performed to address the hypotheses and research questions as well as assumptions that must be addressed prior to analysis.

Descriptive Characteristics of Participants

All participants of the current research study were at least 18 years of age and indicated so by consenting to participate in the research study as described in the consent form in Appendix C. Following invitations to participate, two institutions provided responses indicating an interest; a community college in Ohio (COLLA) and a 4-year public university in Florida (COLLB). The survey instrument was distributed to a random sample frame of the target population (n = 5,963). A response rate of approximately 8.4% (n = 500) was received. Of this random sample, n = 3,211 respondents were from COLLA with a response rate of 8.1% (n = 260) and a random sample of n = 2,572 respondents from COLLB with a response rate of 9.3% (n = 240). However, 37 incomplete cases were removed from the dataset. The remaining sample (n = 463) was used to further prepare the data for analysis. Notably, to be 95% confident in the percentages of the responses of respondents to be representative of the target population with a margin of error of 5%, the recommended sample size was *n* = 375 (i.e., assuming a total combined population of *N* = 15,000 from both institutions; CheckMark, 2019). Based on these indices, a sample size of *n* = 463 was acceptable. A display of the overall demographic information is in Table 1.

More respondents were from COLLA (52.1%, *n* =241) and consisted of those who attempted or completed a Learning Support Mathematics (LSMATH) course. A sample of *n* = 222 respondents were from COLLB. These respondents either attempted or completed one of the four college level gateway courses: Intermediate Algebra (INTERM), College Algebra (ALGEBRA), Finite Mathematics (FINITE) or Pre-Calculus Algebra and Trigonometry (PRECAL). Over twice as many respondents (63.9%, *n* = 296) completed their college level mathematics course or LSM course in the first semester, 15.8% (*n* = 73) needed two semesters, and 14.3% (*n* = 66) needed three or more semesters.

Overall, there were over three times as many female respondents (75.4%, *n* = 349) than male respondents (22.2%, *n* =103). More students in the 18 – 24 age range (66.7%, *n* = 309) participated in the research study. While there was more representation of White respondents (62.6%, *n* = 290) than any other ethnic group, there were approximately equal number of Black/African American (11.9%, *n* = 55) and Hispanic/Latino (12.5%, *n* = 58) respondents, with less than 6% representation of the other ethnic groups. Additionally, 3.5% of respondents identified as Other (e.g., biracial [Black/White, White/Asian, Black/Indian, and Arab/mixed raced] etc.).

Table 1: Overall Demographics

Variable	Sample Size (n)	Percentage (%)
Gender		
Female	349	75.4
Male	103	22.2
Age		
18 – 24	309	66.7
25 – 31	59	12.7
32 – 38	34	7.3
39 – 45	23	5
46 – 52	23	5
53 or over	11	2.4
Ethnicity		
American Indian/Alaska Native	3	0.6
Asian	24	5.2

Table 1 Continued

Variable	Sample Size (*n*)	Percentage (%)
Black/African American	55	11.9
Hispanic/Latino	58	12.5
Native Hawaiian/Other Pacific Islander	2	0.4
Other	16	3.5
White	290	62.6
College		
COLLA	241	52.1
COLLB	222	47.9
Course		
LSMATH	241	52.1
INTERM	19	4.1
ALGEBRA	90	19.4
FINITE	46	9.9
PRECAL	67	14.5

Table 1 Continued

Variable	Sample Size (n)	Percentage (%)
Semester		
1 semester	296	63.9
2 semesters	73	15.8
3 or more semesters	66	14.3

Descriptive Characteristics by College

Given the design of the research study, a breakdown of demographic information by college was necessary. There remained a disproportionate number of respondents by age, gender, and ethnicity between the colleges. In terms of age however, more younger respondents were from COLLB (age group [18 – 24], 95.5%, *n* = 212) than COLLA (age group [18 – 24], 40.2%, *n* = 97). COLLA had a fair representation of respondents age 25 – 52 (61.3%, *n* = 131) with 4.1% 53 years of age or older. The percentage of female and male respondents by college was approximately the same as the overall percentage (e.g., COLLA: female [75.9%, *n* = 183] and COLLB: female [74.8%, *n* = 166]). This was also true for ethnicity. There was more representation of White respondents (COLLA [73%, *n* = 176], COLLB [51.4%, *n* = 114]) than any of the other ethnic groups. On the other hand, there was more diversity in ethnicity at COLLB than COLLA. Of the minority groups, there was an approximately equal number of Black/African American respondents from both colleges: COLLA (11.2%, *n* = 27) and COLLB (12.6%, *n* = 28). Lastly, more Hispanic/Latino and Asian respondents were from COLLB: (23%, *n* = 51) and (8.1%, *n* = 18) respectively (see Table 2).

Recruitment

Recruitment of respondents began with an initial letter (Appendix B) to representatives of both community colleges and 4-year colleges and universities. The institutions either participated in one of the six NCAT program initiatives discussed in Chapter 2 (NCAT, 2005) or were invited to participate as a result of having redesigned specific mathematics courses or programs using the E-Model approach for course instruction. The initial letter was to determine whether potential institutions were currently using the E-Model design. These representatives

Table 2: Demographics by College

	College			
	COLLA		COLLB	
Variable	Sample Size (*n*)	Percentage (%)	Sample Size (*n*)	Percentage (%)
Gender				
Female	183	75.9	166	74.8
Male	55	22.8	48	21.6
Age				
18 – 24	97	40.2	212	95.5
25 – 31	54	22.4	5	2.3
32 – 38	31	12.9	3	1.4
39 – 45	23	9.5	0	0.0
46 – 52	23	9.5	0	0.0
53 or over	10	4.1	1	0.5
Ethnicity				
American Indian[a]	3	1.2	0	0.0

Table 2 Continued

	College			
	COLLA		COLLB	
Variable	Sample Size (*n*)	Percentage (%)	Sample Size (*n*)	Percentage (%)
Asian	6	2.5	18	8.1
Black/African American	27	11.2	28	12.6
Hispanic/Latino	7	2.9	51	23.0
Native Hawaiian[b]	1	0.4	1	0.5
Other	8	3.3	8	3.6
White	176	73	114	51.4
Semester				
1 semester	133	55.2	163	73.4
2 semesters	43	17.8	30	13.5
3 or more semesters	48	19.9	18	8.1

[a] Includes Alaska Native, [b] Includes Other Pacific Islander

were Mathematics Department Deans, Institutional Research, or Vice Presidents of Academic Affairs.

Several months into the recruitment process, the researcher had received one confirmation from a community college. By this time, others had not followed-up or had discontinued the E-Model design or was not interested in the research study. After conversations with the dissertation Chair, the decision was made to extend the research to 4-year colleges and universities. Two universities were initially contacted. The researcher later received confirmation to participate by one of them. Applications to the IRBs of both the community college and university were completed, which letters of approval from both institutions were submitted with the IRB application at the University of Tennessee Knoxville (UTK).

Consent and Incentive

A random sample of the target population of actively enrolled students at each institution was invited to participate in the current research study through e-mail. The recruitment letter (Appendix A) informed respondents of the description and purpose of the research study and expectations. Participants were informed that their participation was voluntary. All had met the age requirement of at least 18 years of age.

To comply with both the UTK and federal guidelines for research involving human subjects, the consent form described the research, participants' involvement, risks, benefits, and incentive (Appendix C). Participants had the option to participate in a drawing for the chance to receive one of several Amazon gift cards worth $25 or $75 stipulated by incentive guidelines at the respective institutions. Participants were provided with contact information of the researcher and the IRB compliance officer at UTK for questions or concerns regarding the research study.

Adopted Items from other Instruments

The adoption of the initial 44 items that composed the EMMS was from survey instruments that were designed to measure levels of motivation and that had been shown to be valid and reliable. The items were a measure of more autonomous levels of extrinsic and intrinsic motivation as defined by SDT with an internal locus of control (Ryan & Deci, 2000). The purpose for the adoption of the items was to assess whether the E-Model learning environment was supportive of students' BPNS, which defined SDT. Additionally, the current section discussed each instrument for which items were adopted that included information about the validity of the internal structure of the items of the instruments and the consistency of the reliability of the subscale factors that composed the adopted items from the respective instruments.

The Learning Support Mathematics Program Perceptions Instrument (LSMPPI) was a 38-item instrument developed by the researcher and used as part of an evaluation project of a Learning Support Mathematics (LSM) program. The program had a structural design that mirrored the E-Model learning environment but included a classroom learning component that was more student-centered and promoted the development of conceptual understand of mathematics (Etheridge, Monroe-Ellis, & Tankersley, 2014). The LSMPPI was composed of three subscales: *Technology Assessment Scale* (TAS-10, 2-factors), *Learning Environment Assessment Scale* (LEAS-15, 3-factors), and the *Motivation Assessment Scale* (MAS-13, 3-factors) where each could be used together or separately. An investigation of the validity of the internal structure was examined using Principal Axis Factor (PAF) extraction and Promax rotation with sample size n = 228. These were suggested methods when data were assumed to be correlated (Osborn, 2014) and violated the assumption of multivariate normality (Gaskin &

Happell, 2014). Exploratory Factor Analysis (EFA) results indicated parsimonious solutions of the LSMPPI and adequate internal consistency of the reliability using Cronbach's alpha ($\alpha = .92$) for the MAS-13 intrinsic motivation 7-item factor that was used in the current study.

The current study adopted all seven items from MAS-13 that measured higher levels of autonomous motivation for a couple of reasons: (1) the construct can be easily applied to measure higher levels of autonomy than the other factors, (2) the construct can be further assessed as a valid and reliable measure of higher levels of autonomous motivation (e.g., identification, integration or even intrinsic motivation) as defined by SDT (Ryan & Deci, 2000; 2017). Table 3 consists of the original items from the LSMPPI and the revised items for the EMMS. These items were measured on a 7-point Likert scale ranging from 1 (Strongly disagree) to 4 (Somewhat agree) to 7 (Strongly agree).

The Intrinsic Motivation Inventory (IMI; Ryan, 1982) was originally used in a laboratory setting to assess the motivation of children to complete puzzle related tasks. The IMI was a 45-item instrument with seven subscales (SDT, n.d.). These were "interest/enjoyment, perceived competence, value/usefulness, effort, felt pressure and tension, perceived choice"; and relatedness. The internal structure of the IMI was assessed and deemed valid using Confirmatory Factor Analysis with adequate Cronbach alpha coefficients, reported to be approximately .79 (McAuley et al., 1989). The instrument was designed to measure the extent to which an individual internalized an activity (the process of transitioning from being externally motivated to becoming more internally motivated) and becoming self-regulators of the activity that the individual regarded as valuable or useful (Deci et al., 1994).

Table 3: Modified LSMPPI items Adopted for the EMMS

LSMPPI Items – Motivation	**New Items in EMMS-ID**
#16. As a result of enrolling in the program, I appreciated mathematics more.	#14. The E-Model environment helped me gained a greater appreciation for mathematics.
#18. I have gained life-long learning skills.	#10. The E-Model environment helped me gain life-long learning skills.
#20. As a result of enrolling in the program, I have increased my mathematical communication skills.	#6. The E-Model environment helped me improve my mathematical communication skills (*in written and verbal forms*).
#22. As a result of enrolling in the program, I am confident in my abilities to do mathematics.	#2. The E-Model environment helped me increase my confidence in my abilities to do mathematics.
#24. As a result of enrolling in the program, the workload prepared me for college level work.	#18. The E-Model environment prepared me for college level course work.

Table 3 Continued

LSMPPI Items – Motivation	**New Items in EMMS-ID**
#26. As a result of enrolling in the program, I took more ownership of my learning.	#13. I felt a greater sense of ownership of what I was learning in the E-Model environment.
#28. In a program like this, I preferred course material that aroused my curiosity, even if it is difficult to learn.	#19. Learning mathematics in an E-Model environment aroused my curiosity.

#Placement in scale

According to Schuttle et al (2017) the instrument was later used in experiments to assess higher levels of autonomous motivation and self-regulation. The researchers adopted the value/usefulness subscale for a research project that focused on assessing medical students' motivation and competence for training in a student-centered learning environment. Results indicated high internal consistency reliability ($\alpha = .92$) for the subscale.

The current study adopted and slightly modify all nine of the value/usefulness subscale items from the activity perception questionnaire used in an internalization study (Deci et al., 1994). The 25-item questionnaire was one of several versions developed in the IMI (SDT, n.d.). Table 4 consists of the original items from the IMI and the revised items for the EMMS. These items were measured on a 7-point Likert scale ranging from 1 (Not at all true) to 4 (Somewhat true) to 7 (Extremely true).

The Basic Psychological Need Satisfaction Scale (BPNS) was adopted from a broad scale used to measure workplace satisfaction (Ilardi et al., 1993; Kasser, Davey, & Ryan, 1992). The 21-item scale had been shown to have adequate internal structure and internal consistency reliability for each of the constructs (Baard, Deci, & Ryan, 2004; Deci et al., 1993; Gagne, 2005). Deci et al. (2001) reported satisfactory reliability values of the constructs: autonomy (7-items; $\alpha = .79$), competence (6-items; $\alpha = .70$), and relatedness (8-items; $\alpha = .70$). The internal structure and consistency of the subscales were supported in a recent study with similar Cronbach's alpha coefficients ($\alpha > .70$; Sevari, 2017).

The current study adopted and modify four of the six competence items and all eight of the relatedness items. The competence items were added to the sub-group of items in Appendix D designed to measure the extent to which a student was motivated to learn mathematics in an E-Model environment. These learning environment items were to measure students' levels of

Table 4: Modified IMI items Adopted for the EMMS

IMI Items – Value/Usefulness	**New Items in EMMS**
#1. I believe that doing this activity could be of some value for me.	#28. I believe that using a Computer Learning System (CLS) could be of some value for me.
#4. I believe that doing this activity is useful for improved concentration.	#29. I believe that a CLS is useful for improved concentration.
#6. I think this activity is important for my improvement.	#30. I think that using a CLS is important for my improvement in learning mathematics.
#10. I think this is an important activity.	#31. I think using a CLS is a worthwhile technology.
#13. It is possible that this project could improve my studying habits.	#32. I think using a CLS would improve my study habits.

Table 4 Continued

IMI Items – Value/Usefulness	**New Items in EMMS**
#16. I am willing to do this activity again because I think it is somewhat useful.	#33. I am willing to use a CLS again because I think it is useful for learning math.
#19. I believe doing this activity could be somewhat beneficial for me.	#34. I believe that using a CLS could be beneficial for learning mathematics.
#21. I believe doing this activity could help me do better in school.	#35. I believe using a CLS could help me do better in my college level math course.
#25. I would be willing to do this activity again because it has some value for me.	#36. I would be willing to use a CLS again because it has some value for me.

#Placement in respective scale

autonomy, competence, and intrinsic motivation. Table 5 lists the selected items that best measured the construct in an E-Model learning environment. These items were measured using 7-point Likert scale ranging from 1 (Strongly disagree) to 4 (Somewhat agree) to 7 (Strongly agree). Additionally, the relatedness items consisted of the sub-group of items in Appendix D designed to measure the extent to which students feel a connection with the instructor/tutor in the E-Model environment. The relatedness items were measured on a 7-point Likert scale ranging from 1 (Not at all true) to 4 (Somewhat true) to 7 (Very true). These BPNS items must be modified to reflect the domain in question (CSDT, 2019).

The Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991) was designed to measure college students' motivations and their use of different "self-regulated learning strategies". The original version consisted of 81 items that were assessed for construct validity and reliability. The motivation 5-factor solutions consisted of 31 items with Cronbach alpha coefficients ranging from .62 to .93. The different learning strategies 9-factor solutions consisted of 50 items with Cronbach alpha coefficients of the factors ranging from .52 to .80. The 15 scales of the MSLQ were designed to be used together or separately (Pintrich et al., 1991). The MSLQ has since been the most commonly used instrument for assessing motivation and self-regulated learning strategies (Chow & Chapman, 2017).

The current study adopted and slightly revised eight of the 12 items designed to measure metacognitive learning strategies. These strategies were one of the 9-factor solutions of the overall metacognitive strategies for learning. Metacognitive strategies were composed of "planning, monitoring, and regulating activities" (Pintrich et al., 1987). Table 6 consists of the original items from the MSLQ and the revised items for the EMMS. The original Cronbach's alpha of .79 for the 12 items (Pintrich et al., 1991) was the same as the Cronbach's alpha in a

Table 5: Modified BPNS items Adopted for the EMMS

Competence	
BPNS Items	**EMMS Items**
#3. Often, I do not feel very competent. R	#4. I often did not feel very competent learning math in an E-Model environment. R
#10. I have been able to learn interesting new skills recently.	#8. I was able to increase my knowledge of math skills in an E-Model environment.
#13. Most days I feel a sense of accomplishment from what I do.	#12. I felt a sense of accomplishment while learning math in an E-Model environment.
#19. I often do not feel very capable. R	#16. I often did not feel capable of learning in an E-Model environment. R

Relatedness	
BPNS Items	**EMMS Items**
#2. I really like the people I interact with.	#20. I liked the instructor/tutors that I came in contact within the E-Model environment.

Table 5 Continued

Relatedness	
BPNS Items	**EMMS Items**
#6. I get along with people I come into contact with.	#21. I got along with the instructor/tutors I came in contact within the E-Model environment.
#7. I pretty much keep to myself and don't have a lot of social contacts. R	#22. I kept to myself and didn't have a lot of contact with the instructor/tutors in the E-Model environment. R
#9. I consider the people I regularly interact with to be my friends.	#23. I considered the instructor/tutors I regularly worked with in the E-Model environment to be my friends.
#12. People in my life care about me.	#24. The instructor/tutors in the E-Model environment cared about me.

Table 5 Continued

Relatedness	
BPNS Items	**EMMS Items**
#16. There are not many people that I am close to. R	#25. There were not many instructor/tutors in the E-Model environment that I connected with. R
#18. The people I interacted with regularly do not seem to like me much. R	#26. The instructor/tutors in the E-Model environment that I worked with did not seem to like me much. R
#21. People are generally pretty friendly towards me.	#27. The instructors/tutors in the E-Model environment were friendly towards me.

R = Reverse code, #Placement in respective scales

Table 6: Modified MSLQ items Adopted for the EMMS

MSLQ Items – Strategies for Learning	New Items in EMMS
#41. When I become confused about something I'm reading for this class, I go back and try to figure it out.	#38. When I became confused about a math problem I was working on, I always tried to figure it out on my own.
#44. If course materials are difficult to understand, I change the way I read the material.	#43. I tried to change my approach to learning the concepts when they were difficult to understand.
#54. Before I study new course material thoroughly, I often skim it to see how it is organized.	#39. Before studying new concepts, I often skimmed the material to see how it was organized.
#55. I ask myself questions to make sure I understand the material I have been studying in this class.	#40. When studying in the E-Model environment, I asked myself questions to make sure I understood the concepts.

Table 6 Continued

MSLQ Items – Strategies for Learning	**New Items in EMMS**
#56. I try to change the way I study in order to fit the course requirements and instructor's teaching style.	#41. I tried to change the way I approached learning math concepts in order to fit the course requirements.
#61. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.	37. When studying in the E-Model environment, I tried to think through a topic to decide what I was supposed to learn from it rather than just reading it over.
#76. When studying for this course I try to determine which concepts I don't understand well.	#42. When studying in the E-Model environment, I tried to determine which concepts I didn’t understand well.
#78. When I study for this class, I set goals for myself in order to direct my activities in each study period.	#44. When studying in the E-Model environment, I tried to set goals for myself in order to direct my activities.

recent study that assessed the construct validation of the factor solutions of the MSLQ using a sample of students at a high school in Singapore (Chow & Chapman, 2017). The other four items were excluded because they were not a good fit for assessing students' level of self-regulation in an E-Model environment. For example, one item stated: "During class time I often miss important points because I'm thinking of other things." This item reflects learning in the traditional educational setting. A learning environment that was not a component of the E-Model. These items were measured on a 7-point Likert scale ranging from 1 (Not at all true) to 4 (Somewhat true) to 7 (Very true).

Additional Newly Developed Items

Table 7 lists items that were designed to measure high levels of autonomy for both extrinsic and intrinsic motivation (Ryan & Powelson, 1991) with an "internal locus of control" (Ryan & Connell, 1989). The development of these eight new items were the result of seven years of observation and conversation between the researcher and students who completed course work in similar types of E-Model learning environments. These items were assessed for content validity and discussed in the next section. The items were measured on a 7-point Likert scale ranging from 1 (Strongly disagree) to 4 (Somewhat agree) to 7 (Strongly agree). Items 1 – 4 were designed to measure intrinsic motivation and items 5 – 8 were designed to measure extrinsic motivation that were more autonomous (Vallerand et al., 1992). These items were included in the sub-group of items that measured students' learning experiences in an E-Model environment (Appendix D).

Item Development Procedure

The process of item development involved two forms of validity. These were content and face validity. The process of item development was carried out in three stages. The first stage focused on a review of pertinent literature related to the constructs to be measured. The review included research on redesigning LSM course(s) and programs from the NCAT website(NCAT, n.d.). The second stage focused on the development of 20 new items following survey research and design techniques (Colton & Covert, 2007). The process also included the adoption and minor revision of 36 items from four surveys: *The Intrinsic Motivation Inventory* (IMI; Ryan, 1982); *The Motivated Strategies for Learning Questionnaire* (MSLQ; Pintrich, et al., 1991); *Basic Psychological Need Satisfaction* scale (BPNS; CSDT, 2019); and *The Learning Support Mathematics Program Perceptions Instrument* (LSMPPI). The LSMPPI was developed by the researcher as part of an evaluation project. The third stage consisted of an assessment of face and content validity through instrument testing and expert review.

An assessment of content validity of the 20 newly developed items was performed by Michael Olson, Ph.D., a professor of social psychology, at UTK. The researcher chose to use Dr. Olson as a reviewer of the newly developed items because he had research experience and knowledge of motivation theory. The researcher communicated with Dr. Olson through e-mail. The list of items were sent, reviewed, and returned with suggestions. He provided expert opinion on whether the 20 items were a measure of more autonomous levels of motivation as defined by self-determination theory (Ryan & Deci, 2000). His review included an assessment of word choice, simplicity of the language used, and checking for double-barreled items. Based on the feedback received, eight of the 20 items were adopted as part of the EMMS.

A review of all 44 items were performed by a sample of students who were enrolled in one of the researcher’s courses that included an LSM component to assess the face validity of the items. These students shared similar characteristics as the participants of the target population

Table 7: New Learning Environment Items to be used in the EMMS

Learning Environment Items
#7. I had a pleasant experience learning mathematics in the E-Model environment.
#15. Learning mathematics in an E-Model environment was an enjoyable experience.
#11. Learning mathematics in an E-Model environment was an interesting experience.
#3. I had a satisfying experience learning mathematics in the E-Model environment.
#1. Learning mathematics at a pace that was suitable for me gave me a sense of choice in the E-Model environment.
#5. I felt a greater sense of control over how I was learning mathematics in the E-Model environment.

Table 7 Continued

Learning Environment Items
#17. I felt like I had a choice learning mathematics in a way that supported my learning abilities in the E-Model environment.
#9. I felt a greater sense of responsibility for my own learning in the E-Model environment.

who attempted or completed an LSM course or module. They were learning support students who used a computer learning system to complete their curriculum and met for class in a lab classroom and computer lab. The items were submitted electronically to students. Students were asked to provide feedback regarding the readability, terminology used, and clarity of sentence structure for understanding. Upon review, items were revised to reflect feedback received.

The final product, *The Emporium Model Motivation Scale* (EMMS; Appendix D) consists of 44 items. The position of items 1 - 19 were randomly selected while the rest were positioned according to the placement from the scale for which they were adopted. These items were assessed for content validity. Table 8 consist of a complete list of all 44 items and the order that the items appeared the EMMS. All items were measured on a 7-point Likert scale. See Appendix D for the specific scales used and the addition of two open-ended items.

Research Procedure

Following IRB approval from UTK and the associated college and university, the researcher began the data collection process. The researcher sent a request to each institution for a representative random sample of the target population. Due to the policy of the university regarding email distribution for research, emails were not allowed to be distributed to other parties. However, the researcher's request was honored by the university, which distributed the emails to the requested student population. Upon receiving the database of e-mails, from the community college, an anonymous link to the survey was created within Qualtrics and distributed to the target population of participants. Notably, the representative random samples consisted of current actively enrolled students who were enrolled in an E-Model course from fall 2016 through Spring 2018 regardless of whether these students completed or attempted to

Table 8: Emporium Model Motivation Scale (EMMS) Items

Emporium Model Motivation Scale (EMMS)
1. Learning mathematics at a pace that was suitable for me gave me a sense of choice in the E-Model environment.
2. The E-Model environment helped me increase my confidence in my abilities to do mathematics.
3. I had a satisfying experience learning mathematics in an E-Model environment.
4. I often did not feel very competent learning math in an E-Model environment. R
5. I felt a greater sense of control over how I was learning mathematics in the E-Model environment.
6. The E-Model environment helped me increase my mathematical communication skills (*communicating in written and verbal forms*).

Table 8 Continued

Emporium Model Motivation Scale (EMMS)
7. I had a pleasant experience learning mathematics in an E-Model environment.
8. I was able to increase my knowledge of mathematics skills in an E-Model environment.
9. I felt a greater sense of responsibility for my own learning in the E-Model environment.
10. The E-Model environment helped me gain life-long learning skills.
11. Learning mathematics in an E-Model environment was an interesting experience.
12. I felt a sense of accomplishment while learning mathematics in an E-Model environment.
13. I felt a greater sense of control over how I was learning mathematics in the E-Model environment.
14. The E-Model environment helped me gain a greater appreciation for mathematics.

Table 8 Continued

Emporium Model Motivation Scale (EMMS)
15. Learning mathematics in an E-Model environment was an enjoyable experience.
16. I often did not feel capable of learning in an E-Model environment. R
17. I felt like I had a choice learning mathematics in a way that supported my learning abilities in the E-Model environment.
18. The E-Model environment prepared me for college level course work.
19. Learning mathematics in an E-Model environment aroused my curiosity.
20. I liked the instructor/tutor that I came in contact within the E-Model environment.
21. I got along with the instructor/tutor I came in contact within the E-Model environment.
22. I kept to myself and didn't have a lot of contact with the instructor/tutor in the E-Model environment. R

Table 8 Continued

Emporium Model Motivation Scale (EMMS)
23. I considered the instructor/tutor I regularly worked with to be my friends.
24. The instructor/tutor in the E-Model environment cared about me.
25. There were not many instructors/tutors in the E-Model environment that I connected with. R
26. The instructor/tutor in the E-Model environment that I worked with did not seem to like me much. R
27. The instructors/tutors in the E-Model environment were friendly towards me.
28. I believe that using a Computer Learning System (**CLS**) could be of some value for me.
29. I believe that a CLS is useful for improved concentration.
30. I think that using a CLS is important for my improvement in learning mathematics.

Table 8 Continued

Emporium Model Motivation Scale (EMMS)
31. I think using a CLS is a worthwhile technology.
32. It think that using a CLS would improve my study habits.
33. I am willing to use a CLS again because I think it is somewhat useful for learning math.
34. I believe that using a CLS could be beneficial for learning mathematics.
35. I believe using a CLS could help me do better in my college level math course.
36. I would be willing to use a CLS again because it has some value for me.
37. When studying in the E-Model environment, I tried to think through a topic to decide what I was supposed to learn from it rather than just reading it over.

Table 8 Continued

Emporium Model Motivation Scale (EMMS)
38. When I became confused about a math problem I was working on, I always tried to figure it out on my own.
39. Before studying new concepts, I often skimmed the material to see how it was organized.
40. When studying in the E-Model environment, I asked myself questions to make sure I understood the concepts.
41. When studying in the E-Model environment, I tried to determine which concepts I didn't understand well.
42. I tried to change my approach to learning the concepts when they were difficult to understand.
43. When studying in the E-Model environment, I tried to set goals for myself in order to direct my activities.

R=Reverse Code

complete an E-Model course.

The specified time periods were chosen to reduce the effects of history and maturation to increase the likelihood of more accurate responses from participants. A reference URL to the survey was created and the anonymous link was distributed to the target population. To maintain anonymity, participants who provided their preferred e-mail address to participate in the drawing, were linked to a database different from the one that contained a link to the survey. The link to the survey remain open for one month. A week prior to the closing of the survey, only participants at the community college received a reminder e-mail to complete the survey. Due to the university policy, only one distribution could be made to respondents.

Following the closure date, the researcher completed the drawing and winners were notified. Thereafter, the data was exported from Qualtrics using an Excel file and saved on a password protected Dropbox folder on the researcher's computer. Both institutions were informed that the data would not be deleted but used for educational purposes and potentially prepared to be published or presented at conferences.

Planned Analysis: Data Cleaning

For general data cleaning, the researcher followed recommendations by Morrow and Skolits (2016) in which they identified twelve steps for cleaning the data and preparing it for both simple analyses (i.e., *t*-tests and simple regression) and more advanced analyses (i.e., MANOVA and Multiple Regression). This approach included the development of an initial codebook consisting of all variables from the data as well as newly developed variables. The codebook was used as a reference tool (coding of variables, labeling, and scale types). Initial analysis of all variables were run using frequencies, percentages, and histograms to check for a variety of possible issues (missing data, checking for outliers, coding issues, spelling errors etc.).

Preparations were made to assign new variable names for ease analysis and reverse coded variables labeled with an R in Appendix D. New IVs were created and discussed in more detail in Chapter 5. Given the issue with unequal samples sizes of the IVs, the researcher relied on the Levene's test of homogeneity of variances (in ANOVA) to determine whether the variance of the IVs were equal across the groups.

Frequencies were run on all variables to obtain descriptive statistics, and normality indicators (skewness and kurtosis) on all scale variables. Outliers were examined following EFA and the development of standardized factor score estimates prior to carrying out further analyses sensitive to outliers. Furthermore, outliers will be winsorized to ±3 standard deviation of the mean in the event outliers are present. To address outliers, standardized scores were created for all DVs. Frequencies, percentages, histograms, and stem and leaf plots were used to examine outliers.

Garson (2012) noted that "correlation, least-squares regression, factor analysis, and related linear techniques were relatively robust against non-extreme deviations from normality provided errors are not severely asymmetric" (p. 17; referencing Vasu, 1979), which may result from extreme outliers. Regardless, normality assumption testing was carried out. The researcher skimmed graphics (the histogram and normal Q-Qplot or probability plot), using descriptive statistics, and checked skewness and kurtosis to examine normality (Hazzi & Maldaon, 2015).

A case for normality was determined when the mean, median, and mode values of the scale variables were approximately the same and histograms that appeared to be bell-shaped (Hazzi & Maldaon, 2015; Tabachnick & Fidell, 2013). When the data were clustered around the line of a P-Plot and Q-Qplot, a case for normality was determined as well (Garson, 2012; Tabachnick & Fidell, 2013). Dividing the skewness and kurtosis values by the respective standard errors was used to determine satisfactory skewness and kurtosis given that the computed value was within ± 2 standard deviations of the mean (Hazzi & Maldaon, 2015). If non-normality was detected, a more stringent alpha was used. Following this process, final frequencies and descriptive statistics were run on all variables to ensure all issues had been addressed.

Conducted Analysis: Hypotheses and Research Questions

The current section begins with a description of the analyses to be run for answering the hypotheses introduced earlier. These were:

1. The Emporium Model Motivation Scale would yield parsimonious factor solutions and be a valid measure of autonomous motivation.
2. The Emporium Model Motivation Scale would yield satisfactory internal consistency reliability of factor solutions using Ordinal Omega Coefficient $\omega \geq .70$.

Discussion then addressed the analyses to be run for the research questions that followed. These were:

1. Are there differences in college on the EMMS factors?
2. Are there differences in type of course (Intermediate Algebra, College Algebra, Finite Mathematics, and Pre-Calculus) on the EMMS factors?
3. Are there differences in age on the EMMS factors?
4. Are there differences in semester on the EMMS factors?
5. Are college, course, age, and semester predictors of the EMMS factors?

Concurrent discussion focused on the necessary assumptions that must be satisfied for specific analyses.

Hypothesis 1 examined the construct and convergent validity of the EMMS items. The *identified regulation* subscale of the *Academic Motivation Scale* (AMS; Vallerand et al., 1992) determined convergent validity of the derived factors of the EMMS. Identified regulation was one of the four levels of motivation on the continuum of extrinsic motivation that measured more moderate to high levels of autonomy (Ryan & Deci, 2000; 2017). The AMS was a 28-item 7-factor scale designed to measure academic motivation assessing the continuum of motivation from amotivation to intrinsic motivation. An examination of the identified regulation subscale was found to be statistically significant and positively correlated with autonomy-supportive latent traits (Vallerand, et al., 1993). The internal consistency of the reliability was sufficient for all subscales ranging from .72 to .91 with a Cronbach's alpha for the identified regulation subscale of .72 on the pre-test and .78 on the post-test. In assessing academic motivation, with respects to identified regulation, respondents were asked: Why do you go to college? A response to the question consisted of four items (e.g., "Because I think college will help me better prepare for the career I have chosen"). The items were measured on a 7-point Likert scale (1-Corresponds not at all to 4-Corresponds moderately to 7-Corresponds exactly). Notably, the validity of the internal structure and consistency of the reliability had been sustained in a more recently study with a reported Cronbach's alpha of .79 (Liu, et al., 2017). See Appendix E for a list of the AMS identified regulation 4-item subscale.

Correlational analyses were performed to assess convergent validity. The criterion for establishing convergence between the factors of the EMMS and the subscale factor AMS was determined by positively and statistically significant correlations defined by Cohen's effect size values for product-moment correlations (i.e., r = .10 [small], .30 [medium], and .50 [large]; Cohen, 1992). One assumption that was addressed for correlational analysis (as well as other analyses) was the assumption of linearity of associated variables (Ott & Longnecker, 2010). A random pattern of the standardized estimates of the dependent variables and standardized residuals examined nonlinearity through visual inspection of the plots and a run of a test of linearity using ANOVA in SPSS (Garson, 2012). If the test of nonlinearity was significant at the .05 level, then a more stringent alpha was used in all analyses that satisfied the assumption of linearity.

There were a variety of options for dealing with missing data that could lead to the deletion of cases or variables with no set guidelines (Osborne, 2014; Tabachnick & Fidell, 2013). However, cases with more that 20% of data missing, were deleted. Given the asymptotic nature of the data in the current research study, Bayesian related approaches were more preferred (Zygmont & Smith, 2014). One such method used was *multiple imputations* (MI). In general, MI was the preferred method due to the fact that the approach tended to reduce but not eliminate bias in the data and created more accurate standard errors (Hazzi & Maldaon, 2015). Given that FACTOR was used to carryout EFA, it handled missing data by using MI. The approach in FACTOR was based on the Hot Deck MI (HD-MI) method (Lorenzo-Seva & Ginkel, 2016). According to Lorenzo-Seva and Ginkel (2016), the HD-MI method was based on the theory of the underlying variables approach (UVA) for ordinal factor analysis and made no distributional assumptions about the missingness of data for the purpose of creating factor score estimates in EFA. The standardized factor score estimates created in FACTOR were used in all other analyses except the analysis for assessing the internal consistency of the reliability of the derived factors. This approach was discussed in more detail in the coming section regarding Hypothesis 2.

The internal structure of the EMMS underwent robust EFA. The robustness of the EFA results were measured by the inclusion of Biased Corrected (BC) Bootstrap 95% CIs for many of the indices produced in FACTOR. FACTOR (a computer program) was downloaded from the internet, which was designed specifically to assess latent traits in EFA (Ferrando & Lorenzo-Seva, 2017). FACTOR had been found to produce compariable results to SPSS (Lorenzo-Seva & Ferrando, 2006). Assumptions specific to EFA were addressed. Multicollinearity and singularity was assessed by reviewing the bivariate correlations generated in FACTOR. As long as bivariate correlations were non-zero, variables could be used in EFA (Baglin, 20l4). However, to avoid multicollinearity, bivariate correlations had to be < 0.90 (Tabachnick & Fidell, 2013). Variables that violated these conditions were deleted. Two measures of factorability were checked. These were: Bartlett's test of sphericity (must be significant), and Kaiser-Meyer-Olkin (KMO) test with a value at least 0.80 (Beaver's et al., 2013; Tabachnick & Fidell, 2013).

Because data in the social and behavioral sciences were likely correlated (Costello & Osborne, 2005; Osborne, 2014), Oblique methods of extraction and rotation were used. Bivariable correlations between the derived factors supported this claim. Given that Likert scale data were most likely asymmetric and having excess of skewness and kurtosis, violation of univariate and multivariate normality were expected. For this reason, polychoric correlations were used to factor analyze the data with Unweighted Least Squares extraction (Gaskin & Happell, 2014) and Promax rotation.

Prior to extracting factors, multiple methods were used to determine the appropriate number of factors to extract given that no one method was flawless (Courtney, 2013; Osborne, 2014). According to Garrido et al. (2013), features of factor analyzing the data could influence the appropriate number of retained factors. These features included the sample size, correlations, the number of variables per factor, skewness, factor loadings, or whether orthogonal or oblique methods were used. All methods used were explored in FACTOR. These methods were:

Kaiser's criterion (eigenvalues > 1 rule), Velicer's Minimum Average Partial, Horn's Parallel Analysis (MAP and PA respectively; see Courtney, 2013) and Schwarz Bayesian Information Criterion (BIC) dimensionality test (Neath & Cavanaugh, 2012).

Following parsimonious solutions of the EMMS factors, standardized factor score estimates were generated in FACTOR and computed using Bayes *expected a posteriori* (EAP) estimates. These EAP estimates were theoretically justifiable than any other method for generating factor score estimates that involves ordinal factor analysis (Lorenzo-Seva, 2016). Robust EFA in FACTOR allowed for the production of Bootstrap 95% confidence intervals (CI). Bootstrap CIs were computed for specific assessment indices in FACTOR (Ferrando & Lorenzo-Seva, 2017). Given that factor score estimates were indeterminate (i.e., have infinite solutions; DiStefano & Mindrila, 2009), the factor score estimate assessment indices (i.e., the *factor determinacy index* [FDI] and *marginal reliabilities*; Ferrando & Lorenzo-Seva, 2017a) were selected. An FDI index > .90 and marginal reliabilities >.80 were considered acceptable indices to ensure estimates were accurate representations of participants' "true" score response (Ferrando & Lorenzo-Seva, 2017a).

Additionally, the *generalized H* (G-H) Latent and Observed indices were selected in FACTOR in order to assess the generalizability of the factor structure to be replicable across samples or populations. The G-H indices were developed to assess how well a factor was defined by its common items with an acceptable threshold value of > .80 (Ferrando & Lorenzo-Seva, 2017a). More specifically, in reference to the assumption of the underlying variables approach (UVA model for ordinal factor analysis), an H-Latent index greater than .80 indicated how well a common factor was defined by the continuous latent response variables that underly the observed variable, whereas, the H-Observed index was a measure of how well the factor was defined by the observed variable.

Hypothesis 2 examined the consistency of the reliability of the derived factors. The ordinal omega coefficient alpha was used to compute the reliability of each factor. The ordinal coefficient alpha was recommended for studies involving ordinal or Likert scale data (Zumbo et al., 2007). A simulation study completed by Zumbo et al. (2007) reported that the ordinal coefficient alpha produced better estimates of the theoretical reliability than Cronbach's alpha. Results indicated that the ordinal coefficient alpha was least influenced by skewed data with few response categories (range used; 2 – 7) and low magnitude of reliability coefficients (range used; .4 - .9). The ordinal alpha was reported to be an unbiased estimate of the theoretical reliability and did not violate the continuous data assumption (Gadermann & Zumbo, 2012). Ordinal alpha accounted for the fact that ordinal or Likert scale data were most likely skewed. For these reasons, ordinal alpha was used to measure the internal consistency of the reliability of the derived factors of the EMMS.

Following validation analysis in FACTOR, the internal consistency of the reliability was computed using ordinal omega coefficient alpha in R. The original data containing the variables derived from the EFA analysis were read in R for which missing data were handled using the Multivariate Imputation by Chained Equations (MICE; Zygmont & Smith, 2014). The imputations were created using predictive mean matching; another Bayesian approach. The MBESS package (Dun et. al., 2014) was used to compute the ordinal omega coefficients for each factor.

Research Questions (1through 4) required the use of Multivariate Analysis of Variance (MANOVA) because multiple dependent variables (factors of the EMMS; DVs) were compared in one analysis (Huck, 2012). The independent variables (IVs) of the research questions were college, course, age, and semester respectively. The IVs were used to determine whether differences existed when comparing the levels of the EMMS factors.

Specific assumptions were checked before using MANOVA. These were multivariate outliers, linearity, homogeneity of both variance and variance-covariance matrices, and multicollinearity (Tabachnick & Fidell, 2013). Although outliers were checked during the data cleaning stage of the current research, multivariate outliers were assessed because there were multiple DVs in each analysis, which the Mahalanobis distance test (in SPSS linear regression) was used to examine multivariate outliers and were investigated by identifying the highest distance squared values among cases (Garson, 2012). Linearity was checked as discussed in the Hypothesis 1 section. Homogeneity of variance was investigated as discussed in the Planned Analysis: Data Cleaning section regarding unequal sample sizes. Box's *M* test (a General Linear Model [GLM] analysis in SPSS) was used to investigate homogeneity of variance-covariance, which was considered a strict test sensitive to violations of multivariate normality (Garson, 2012). A more stringent alpha of $\alpha = 0.025$ was used, which indicated unequal variances between DVs. Tabachnick and Fidell (2013) suggested $\alpha \leq 0.025$ be used for "moderate violation" and $\alpha \leq .01$ for "severe violation" (p. 86). DVs that were too highly correlated (typically $r > 0.80$; Garson, 2012) were signs of multicollinearity and were examined using collinearity diagnostics in SPSS regression. A tolerance level (< 0.20) and variance inflation factor (VIF; cut off > 5) was an indicated of multicollinearity (Garson, 2012). Highly correlated DVs were dropped from the analysis and single level ANOVAs were computed for each DV (Tabachnick & Fidell, 2013).

A One-Way Between-Subjects MANOVA was run to determine if there were differences between the linear combinations of the DVs with respect to the IVs to answer research questions (1 through 4) in the respective analyses. The analyses were considered Between-Subjects because participants were in different groups of the IVs and One-Way because there was only one IV analyzed in each group (Huck, 2012). Significance was determined by two MANOVA tests of the omnibus null, which represented no differences between the linear combinations of the DVs in the population. Wilk's lambda was used if assumptions were not violated and Pillai's trace if any one assumption was violated (Tabachnick & Fidell, 2013). Significant results were determined using $\alpha \leq .05$ or a more stringent alpha level was used. For IVs with at least three levels, a Post hoc test was run to determine exactly which variables differed (Huck, 2012).

Research Question 5 enquired the use of Standard Multiple Regression (MR) because the researcher was interested in the unique contributions of each IV (analyzed simultaneously) on each DV at a time (Keith, 2015). Another reason was that MR required less observations than any of the other methods (Sequential and Stepdown; Cohen et al., 2003). The goal was to determine the amount of unique variance of the DV that was predicted by the IVs, in which the squared semi-partial correlations (sr_i^2) were used to explain this effect, while controlling for other IVs in the analysis (Cohen et al., 2003).

Assumptions critical to MR were these: normality, linearity, multicollinearity, homoscedasticity, and independence of residuals. Means for investigating the first three assumptions were previously discussed. Homoscedasticity was examined by skimming scatter plot residuals, which assessed whether the variances of the residuals were equal; a technique similar to homogeneity of variance in MANOVA (Cohen et al., 2003). Lastly, the Durbin Watson (DW) test investigated independence of residuals to determine whether participants of the IVs were unique to a respective variable (Keith, 2015). According to Keith (2015), sufficient DW values were < 2, if violated more advanced methods should be used (i.e., multilevel or hierarchical linear modeling). Notably, linearity was most critical of these assumptions because violation threatened the meaning of parameter estimates, while other assumptions obscured interpretation (Cohen, et al., 2003). In addition to using a more stringent alpha level, IVs that violated linearity were either increased in power or removed from the analysis (Cohen, et al., 2003).

CHAPTER 4: ANALYSIS OF DATA

Data Cleaning Approach: Prior to EFA

Data cleaning was completed in two stages; prior to and following EFA due to the fact that some data cleaning techniques were not necessary to carry out the analysis on Oblique (correlated) data when using polychoric correlations as the factor extraction method. However, all issues of data cleaning were addressed as discussed in the Methods chapter. Initial data cleaning procedures included running frequencies of all variables to prepare for the development of the codebook and analysis plan, which were used as reference guides. The codebook included all initial and newly developed variables, items, and the corresponding response scales. The analysis plan consisted of all analyses to be run for organizational purposes.

Following these developments, specific item variables, that were negatively worded, were recoded and then the data were prepared for initial validation of scale variables to identify possible factors. There were no more than 3.3% of cases or variables with missing data. Unlike cases, no variables were deleted initially. All variables with missing data were set to system missing and recoded as 99 (missing), which was needed to run FACTOR for EFA. Additional procedures for addressing assumptions and issues of data cleaning were discussed in later sections, in detail, with the introduction of specific analyses that addressed a hypothesis or research question.

Hypotheses and Research Questions

Discussion of data analysis initially addressed the following two hypotheses (*H*).

1. The Emporium Model Motivation Scale would yield parsimonious factor solutions and be a valid measure of autonomous motivation (*H1*).

2. The Emporium Model Motivation Scale would yield satisfactory internal consistency reliability of factor solutions using Ordinal Omega Coefficient $\omega \geq .70$ (*H2*).

Thereafter, data analysis then addressed the following five research questions (*RQ*).

1. Are there differences in college on the EMMS factors (RQ1)?
2. Are there differences in type of course (Intermediate Algebra, College Algebra, Finite Mathematics, and Pre-Calculus) on levels of the EMMS factors (RQ2)?
3. Are there differences in age on the EMMS factors (RQ3)?
4. Are there differences in semester on the EMMS factors (RQ4)?
5. Are college, course, age, and semester predictors of the EMMS factors (RQ5)?

Hypothesis (H1)

Construct validity (internal structure). The researcher was interested in completing the first phase of the validation of the EMMS. The instrument contained 44 items (see Appendix D). These items were a measure of more autonomous levels of motivation. The items are a representation of the effectiveness of learning mathematics in a course designed using the E-Model approach, which led to the following hypothesis.

The Emporium Model Motivation Scale would yield parsimonious factor solutions and be a valid measure of autonomous motivation (H1). Prior to performing EFA, specific assumptions and issues of data clean were addressed. A review of the histograms of each variable were found to deviate from normality with skewness and kurtosis values greater than one in absolute value for several of the variables. At the 0.05 level of significance, Mardia's asymmetric test of skewness and kurtosis showed that skewness was not significant, p =1, while kurtosis was significant $p < .0001$. Both Bartlett's test of sphericity $\chi^2(496) = 14,488.7$, $p = .0001$ and the (KMO) test value = 0.97 (marvelous; Pett, Lackey, & Sullivan, 2003) supported factorability. Additionally, a very precise 95% CI of the Biased-Corrected (BC) bootstrap of the KMO = (0.97, 0.97) suggested the potential factorability across other samples or populations. As a result, specific methods, as discussed in the Methods chapter, were used to explore the latent traits of the 44 items for Oblique data. Furthermore, a review of the Legacy Dialog plots suggested slight to moderate violations of multivariate normality and linearity, which was to be expected. A review of the Normal P-Plots of the regression standardized residuals, suggested slight violation of linearity as well. For these reasons, the polychoric correlation matrix was used to factor analyze the data.

During the initial item development stage, the researcher hypothesized the retention of four factors given that many items were derived from other validated and reliable survey instruments. To support the initial hypothesis, several methods for retaining factors were reviewed These were: Kaiser's eigenvalue > 1 criterion, Velicer's MAP, Horn's PA, and BIC dimensionality test. The more modern methods, BIC, MAP, and PA suggested the retention of three factors when using polychoric correlations. The more commonly used traditional method (i.e., Kaiser's eigenvalue > 1 rule) suggested the retention of four factors. Table 9 lists the eigenvalue (1.18) of the fourth factor was greater than one. Based on these results and the fact that each of the adopted subscale items from other instruments that had been shown to be valid and reliable in several studies, the researcher chose to retain four factors. Additional evidence supporting a 4-factor solution were the *G-H* Latent and Observed indices for assessing generalizability of the derived factor structure listed in Table 12 below.

Data in the social and behavior sciences will most always be correlated to some extent (Osborne, 2014). Significant bivariate correlations of the EMMS factors supported this notion listed in Table 11 below. For these reasons, Oblique methods were used to extract (ULS) and rotate (Promax) factors to further explore the factorability of the items.

After performing EFA using Oblique methods, 12 variables were removed from the analysis. All five reverse coded variables had to be removed (COMPET2-#11, 5-#14 and RELATE3-#22, 6-#25, 7-#26). These variables cross-loaded on-to an additional factor. Initial bivariate correlational analysis of the variables suggested the removal of four variables due to the multicollinearity violation (COMPET7-#29, 8-#30, and 9-#31 and LEARNS3-#34). Three additional variables (LEARNS1-#32 [cross loaded on the computer attitude variable], LEARNS2-#33 [contributed the least amount of communality], and RELATE4-#20 [to improve minimum communality to .53]). The remaining 32 items formed the EMMS (see Table 10). Following the EFA procedure, standardized factor score estimates were computed in FACTOR. Additional data cleaning techniques were performed on the factor score estimates to address the research questions (e.g., addressing outliers, issues of cell sample size, and the collapsing of specific variables).

Autonomy-supportive Learning Environment (AUTOLE). The first factor consisted of a 17-item subscale that accounted for approximately 62.3% of the variance. These items assessed whether the learning environment was autonomy-supportive. Example common items of the subscale were: "The E-Model environment helped me increase my confidence in my abilities to do mathematics." [*competence*], "Learning mathematics at a pace that was suitable for me gave me a sense of choice in the E-Model environment." [*control*], and "I had a satisfying experience learning mathematics in an E-Model environment." [*intrinsic motivation*].

Table 9: Extracted Eigenvalues and Explained % of Variance

Factors	Eigenvalues*	Variance %	Cumulative Variance %
1	**19.94**	62.31	62.31
2	**2.49**	7.79	70.10
3	**1.63**	5.08	75.18
4	**1.18**	3.68	78.85
5	0.82	2.56	

*ULS with Promax rotation in FACTOR

Table 10: EMMS 32-Item 4-Factor Solution

Items	Factors*			
	1	2	3	4
The E-Model environment helped me increase my confidence in my abilities to do mathematics.	**0.912**	-0.100	0.068	-0.028
Learning mathematics at a pace that was suitable for me gave me a sense of choice in the E-Model environment.	**0.911**	-0.016	-0.033	-0.081
I had a satisfying experience learning mathematics in an E-Model environment.	**0.910**	-0.101	0.114	-0.058
I felt a greater sense of control over how I was learning mathematics in the E-Model environment.	**0.891**	-0.011	-0.062	0.099

Table 10 Continued

Items	Factors*			
	1	2	3	4
I had a pleasant experience learning mathematics in an E-Model environment.	**0.890**	0.063	0.069	-0.114
I felt a greater sense of responsibility for my own learning in the E-Model environment.	**0.881**	0.047	-0.281	0.203
I was able to increase my knowledge of mathematics skills in an E-Model environment.	**0.854**	0.018	0.060	-0.024
I felt a greater sense of control over how I was learning mathematics in the E-Model environment.	**0.849**	-0.096	0.074	-0.052

Table 10 Continued

Items	Factors*			
	1	2	3	4
I felt a sense of accomplishment while learning mathematics in an E-Model environment.	**0.832**	-0.038	0.104	0.047
Learning mathematics in an E-Model environment was an interesting experience.	**0.815**	0.038	-0.112	0.122
Learning mathematics in an E-Model environment was an enjoyable experience.	**0.733**	0.056	0.248	-0.118
The E-Model environment helped me gain a greater appreciation for mathematics.	**0.685**	0.071	0.172	-0.036

Table 10 Continued

Items	Factors*			
	1	2	3	4
The E-Model environment helped me gain life-long learning skills.	**0.664**	0.151	0.095	0.027
I felt like I had a choice learning mathematics in a way that supported my learning abilities in the E-Model environment.	**0.644**	0.072	0.248	-0.022
The E-Model environment prepared me for college level course work.	**0.634**	0.055	0.194	0.055
The E-Model environment helped me increase my mathematical communication skills (*communicating in written and verbal forms*).	**0.617**	0.029	0.198	-0.018

Table 10 Continued

Items	Factors*			
	1	2	3	4
Learning mathematics in an E-Model environment aroused my curiosity.	**0.540**	0.074	0.244	0.031
I liked the instructor/tutor that I came in contact with, in the E-Model environment.	0.053	**0.957**	-0.025	-0.083
I got along with the instructor/tutor I came in contact with, in the E-Model environment.	0.053	**0.937**	-0.102	0.031
The instructor/tutor in the E-Model environment cared about me.	-0.089	**0.794**	0.147	-0.022
The instructors/tutors in the E-Model environment were friendly towards me.	-0.007	**0.784**	0.009	0.039

Table 10 Continued

Items	Factors*			
	1	2	3	4
It think that using a CLS would improve my study habits.	0.075	-0.066	**0.866**	0.029
I think that using a CLS is important for my improvement in learning mathematics.	0.096	-0.023	**0.858**	0.024
I believe that a CLS is useful for improved concentration.	0.038	0.042	**0.849**	0.004
I am willing to use a CLS again because I think it is somewhat useful for learning math.	0.142	0.023	**0.800**	0.012
I think using a CLS is a worthwhile technology.	0.124	-0.021	**0.760**	0.086

Table 10 Continued

Items	Factors*			
	1	2	3	4
I believe that using a Computer Learning System (**CLS**) could be of some value for me.	0.203	0.022	**0.724**	0.017
I tried to change my approach to learning the concepts when they were difficult to understand.	0.018	-0.048	-0.033	**0.903**
When studying in the E-Model environment, I asked myself questions to make sure I understood the concepts.	0.033	-0.100	0.049	**0.847**
I tried to change the way I approached learning math concepts in order to fit the course requirements.	-0.123	-0.011	0.080	**0.783**

Table 10 Continued

Items	Factors*			
	1	2	3	4
When studying in the E-Model environment, I tried to set goals for myself in order to direct my activities.	0.138	0.105	-0.021	**0.668**
When studying in the E-Model environment, I tried to determine which concepts I didn't understand well.	-0.070	0.160	0.175	**0.629**

Note*. **1=Autonomy-supportive learning environment, **2**=Relatedness, **3**=Computer Attitude, **4**=Metacognitive learning strategies

Relatedness (RELATE). The second factor consisted of a 4-item subscale that accounted for approximately 7.9% of the variance. These items assessed the extent to which respondents agreed with the relatability of the instructor/tutor in the learning environment. Example common items were: “I liked the instructor/tutor that I came in contact with-in the E-Model environment.” and “The instructor/tutor in the E-Model environment cared about me.”

Computer Attitude (COMATT). The third factor composed of a 6-item subscale, accounted for approximately 5.1% of the variance. These items assessed the extent to which respondents valued the use of a Computer Learning System (CLS). Sample items were: “I think that using a CLS would improve my study habits.” and “I think that using a CLS is important for my improvement in learning mathematics.”

Metacognitive Learning Strategies (LEARNS). The final factor accounted for the least about of variance, approximately 3.7%, that consisted of a 5-item subscale. These items assessed the extent to which respondents used a metacognitive learning strategy in the learning environment. Sample items were: “I tried to change my approach to learning the concepts when they were difficult to understand.” and “When studying in the E-Model environment, I tried to set goals for myself in order to direct my activities.”

Multivariate normality, linearity, and outliers. To address additional research questions, more data cleaning and assumption testing were performed on the factor score estimates. Rather than exclude any more cases, potential outliers with $> \pm 3$ standard deviations were winsorized (Garson, 2012). These outliers were set to either ± 3 standard deviations from the mean. A total of 19 cases from three factors were changed. These were: RELATE (6 cases), LEARNS (8 cases), and AMS (8 cases).

Multivariate normality and linearity were reassessed on the factor score estimates following EFA. There were no signs of severe violation of these assumptions. The Legacy Dialog plots displayed fairly elliptical shaped scatterplots. Moreover, the Mahalanobis distance test in regression analysis did not suggest any issues with multivariate outliers.

Convergent validity. The Academic Motivation Scale (AMS; Vallerand et al., 1992) was chosen to assess whether the subscale items of the EMMS were representative of higher levels of autonomous motivation. Table 11 displays the bivariate correlations between the EMMS factors and AMS. Results showed that only the relatedness factor produced a positive statistically significant correlation with the AMS factor ($r = 0.11$, $p < 0.05$). Although significant, the effect size based on Cohen's criterion for the product-moment correlation was small. Based on these results, there was not enough evidence to suggest that the other factors were a measure of higher levels of autonomous motivation.

Hypothesis (H2)

Reliability (internal consistency). The internal consistency of the reliability was measured using ordinal omega coefficient alpha (ω). The omega values for each factor were computed using R with 95% CI's. Similar to EFA in FACTOR, missing data was handled in R using the MICE package, while the MBESS package was used to compute the omega coefficients.

The Emporium Model Motivation Scale would yield satisfactory internal consistency of the reliability of factor solutions using Ordinal Omega Coefficient Alpha, $\omega \geq .70$ *(H2).* The internal consistency of the reliability for each subscale was satisfied. The reliability coefficient for AUTOLE ($\omega = 0.98$) had a very precise 95% CI of [0.97, 0.98]. The 17 items were

Table 11: Bivariate Correlations Between the EMMS Factors and AMS (n= 463)

	AUTOLE	COMATT	RELATE	LEARNS	AMS
AUTOLE	1				
COMATT	0.79**	1			
RELATE	0.66*	0.57**	1		
LEARNS	0.53**	0.55**	0.53*	1	
AMS	0.09	0.08	0.11*	0.08	1

Note. **AUTOLE**=Autonomous Learning Environment, **COMATT**=Computer Attitude, **RELATE**=Relatedness, **LEARNS**=Learning Strategies, *p < .05. ** p < .01.

measured on a 7-points Likert scale (i.e., 1=Strongly disagree, 2=Disagree, 3=Slight disagree, 4= Neither agree nor disagree, 5=Slightly agree, 6=Agree, 7=Strongly agree).

The items of the other three common factors were measured on the same 7-point Likert scale (i.e., 1= Not at all true, 2= Untrue, 3= Slightly untrue, 4= Neither true nor untrue, 5= Slightly true, 6= True, 7= Exactly true). These common factors had precise 95% CIs as well. In the case of the RELATE 4-factor subscale, the reliability coefficient was $\omega = 0.91$ with a precise 95% CI of [0.90, 0.92]. In the case of the COMATT 5-factor subscale, the reliability coefficient was $\omega = 0.96$ with a very precise 95% CI of [0.96, 0.97] and the reliability coefficient for the 5-factor subscale LEARNS was $\omega = 0.89$ with a precise 95% CI of [0.88, 0.91].

Factor Score Estimates and Replicability Indices

Factor score estimates indices. To assess accuracy of factor score estimates, both the FDI and marginal reliabilities (MR) were selected in FACTOR. The FDI values for all factors were > 0.90 and ranged between 0.95 – 0.99. The reliability of the factors to be a true estimate of the population score produced MR values > .90. These values ranged from 0.92 – 0.98. (see Table 12).

Construct replicability indices. To assess the potential generalizability of the 4-factor solution, the G-H Latent and Observed indices were selected in Factor. The G-H Latent values for all factors were > 0.80 and ranged from 0.92 – 0.97. The G-H Observed values for all factors were > 0.80 as well. Additionally, Biased Corrected (BC) 95% CI's were computed and suggested the potential for the EMMS to be replicated across samples or other populations. Table 12 also displays these results.

Table 12: Accuracy of Factor Score Estimates and Replicability of Factor Solutions

Index	AUTOLE	COMATT	RELATE	LEARNS
[a]FDI	0.99	0.98	0.98	0.95
MR	0.98	0.97	0.95	0.92
	Latent	Latent	Latent	Latent
[c]G-H	0.98	0.97	0.95	0.92
	(0.96 0.98)	(0.95 0.98)	(0.91 0.96)	(0.77 0.93)
	Observed	Observed	Observed	Observed
	0.92	0.91	0.89	0.85
	(0.84 0.94)	(0.85 0.92)	(0.78 0.90)	(0.65 0.87)

[a]**FDI** = Factor Determinacy Index, [b]**MR** = Marginal Reliability, [c]**G-H** = Construct Replicability, **AUTOLE**=Autonomy-supportive Learning Environment, **COMATT**=Computer Attitude, **LEARNS**=Learning Strategies, **RELATE**=Relatedness

Data Cleaning Approach: Post EFA

Prior to performing any additional analyses, procedures for identifying outliers and addressing cell sample size issues were carried out. Following the development of factor score estimates in FACTOR, frequencies, descriptive statistics, and cross tabulation procedures were performed on the demographic variables (college, course, gender, ethnicity, age, and semester). Respondents who chose “Prefer not to answer” on any demographics were set to system missing and coded 99 (missing) along with other missing values on demographics. The variables included in analyses as IVs were college, course, age, and semester.

Reviewing cross tabulation procedures and performing initial Levene’s test of homogeneity of variance to assess cell sample size, yielded significant results in some cases for course, age, and semester on the EMMS factors. All IVs were recoded to form reference and indicator variables. College was recoded as (COLLEGE): two groups (0=COLLB) and (1=COLLA). Course was recoded as (COURSE): five groups (0=LSMATH), (1=INTERM), (2=ALGEBRA), (3=FINITE), and (4=PRECAL). Age was recoded as (AGE): six groups (0=18-24), (1=25-31), (2=32-38), (3=39-45), (4=46-52), and the last two age group-levels were collapsed into (5=53 or over) because the last group (60 or over) was represented by one respondent.

One-way MANOVA. There were a couple of reasons for choosing to run a MANOVA. There were: a) to protect against making a Type 1 error (i.e., rejecting the null when it is true) by analyzing all DVs in one analysis, and b) to increase the chance of identifying differences that might otherwise go undetected when running single ANOVAs for each DV (Tabachnick & Fidell, 2013). First, assumption tests unique to MANOVA were performed. These were assessing multicollinearity of the DVs, running Levene’s test of homogeneity of variance, and

Box's *M* test of homogeneity of variance-covariance matrices. Following these procedures, initial bivariate correlations of all DVs and IVs were performed to determine whether MANOVA was the best analysis for the data. Results indicated no issues with multicollinearity amongst the DVs. All correlations (< .80) were statistically significant at the 0.05 level with the exception of the IV, SEMESTER. Correlational values between the DVs and SEMESTER ranged from $r = -0.04$ to 0.07, which was an indication that little to no significant differences would be detected given that there was very little to no correlation between the DVs and SEMESTER (Tabachnick & Fidell, 2013). For this reason, it was meaningless to consider this variable in any analysis. Therefore, research question "*Are there differences in semester on levels of the EMMS factors (RQ4)?"* was eliminated from the study.

Are there differences in college on levels of the EMMS factors (RQ1)? Both Levene's test of homogeneity of variance and Box's *M* test of homogeneity of variance-covariance matrices were not significant regarding COLLEGE on the EMMS factors. Table 13 displays the means and standard deviations between these variables.

A One-way MANOVA was conducted to assess the existence of mean differences between COLLEGE on the EMMS factors. The overall result of the omnibus null was significant, $F(4, 458) = 13.494$, $p < .0001$, partial eta² = 0.11. Follow-up One-way Between-Subjects ANOVA tests yielded statistically significant mean differences between COLLEGE on all EMMS factors (see Table 14). More specifically, on the EMMS factor AUTOLE , respondents from COLLA ($M = 0.17$, $SD = 0.98$) felt that the E-Model design was more supportive of their individual autonomy than respondents from COLLB ($M = -0.20$, $SD = 0.90$), which represents a small to medium effect ($d = 0.39$). On the EMMS factor COMATT, respondents from COLLA ($M = 0.17$, $SD = 0.94$) found more value in using a CLS in the

Table 13: Means and Standard Deviations for COLLEGE

DV*	College	Mean[a]	SD	N
AUTOLE	COLLB	-0.20	0.90	222
	COLLA	0.17	0.98	241
COMATT	COLLB	-0.19	0.96	222
	COLLA	0.17	0.94	241
LEARNS	COLLB	-0.19	0.94	222
	COLLA	0.17	0.88	241
RELATE	COLLB	-0.32	0.88	222
	COLLA	0.28	0.90	241

Note. ***DV**= Dependent Variables. [a]standardized mean values

Table 14: One-way ANOVA Tests of Between-Subjects Effects for COLLEGE

DV	F	p	η^2
AUTOLE	17.91	0.0001	0.04
COMATT	15.19	0.0001	0.03
LEARNS	18.25	0.0001	0.04
RELATE	53.13	0.0001	0.10

Note. Significance level, $p < .025$, df=1 and error df = 461.

E-Model learning environment than respondents from COLLB (M = -0.19, SD = 0.96), which represents a small to medium effect (d = 0.38). On the EMMS factor LEARNS, similar to the previous outcomes, respondents from COLLA (M = 0.17, SD = 0.88 utilized more metacognitive learning strategies in the E-Model learning environment than respondents from COLLB (M = -0.19, SD = 0.94) to support learning mathematics, which represents a small to medium effect (d = 0.40). On the EMMS factor RELATE, consistent with previous outcomes, respondents from COLLA (M = 0.28, SD = 0.90) felt more connected to the instructor/tutors in the E-Model learning environment than respondents from COLLB (M = -0.32, SD = 0.88), which represents a medium effect (d = 0.67). Given the statistically significant results, COLLEGE was used as a predictor variable (IV) in the multiple regression analysis to determine unique impact on level of the EMMS factors.

Are there differences in course (Intermediate Algebra, College Algebra, Finite Mathematics, and Pre-Calculus) on levels of the EMMS factors (RQ2)?

Box's M test of homogeneity of variance-covariance matrices was significant with respects to the EMMS factors and COURSE. Levene's test of homogeneity of variances was significant for all EMMS factors with exception to LEARNS. Given these results, the researcher chose to run single level ANOVAs and relied on a more stringent alpha level for moderate violation ($\alpha = 0.025$) to assess differences in means across levels of COURSE on the EMMS factors (Tabachnick & Fidell, 2013). Brown-Forsythe's and Welch's robust F tests of mean differences were used to determine significance given both tests were alternative tests and more robust to violation of Levene's test of homogeneity of variances (Tomarken & Serlin, 1986). Table 15 displays the means and standard deviations of COURSE on the EMMS factors.

Table 15: Means and Standard Deviations of COURSE

Factor	Course	Mean	SD	N
AUTOLE	INTERM	-0.13	1.07	19
	ALGEBRA	-0.24	0.96	90
	FINITE	-0.02	0.72	46
	PRECAL	-0.29	0.88	67
COMATT	INTERM	-0.16	1.16	19
	ALGEBRA	-0.24	1.00	90
	FINITE	0.04	0.71	46
	PRECAL	-0.29	0.99	67
LEARNS	INTERM	-0.08	1.04	19
	ALGEBRA	-0.26	0.95	90
	FINITE	-0.15	1.00	46
	PRECAL	-0.16	0.87	67

Table 15 Continued

Factor	Course	Mean	SD	N
RELATE	INTERM	-0.03	1.13	19
	ALGEBRA	-0.37	0.78	90
	FINITE	-0.16	0.67	46
	PRECAL	-0.44	1.04	67

Four One-way Between-Subjects ANOVA tests were performed. The tests were to determine whether there were mean differences across levels of COURSE based on the EMMS factors. There were no statistically significant mean differences across levels of COURSE on any of the EMMS factors. Table 16 displays the *F* statistics for each of the four EMMS factors across levels of COURSE. For this reason, COURSE was removed as a potential IV or predictor variable on the EMMS factors in the multiple regression analysis.

Are there differences in age on levels of the EMMS factors (RQ3)?

Regarding AGE, Box's *M* test of homogeneity of variance-covariance matrices was significant with respects to the EMMS factors Similar to COURSE, Levene's test of homogeneity of variances was significant for all EMMS factors with exception to LEARNS. As a result, single level ANOVAs were performed using a more stringent alpha level for moderate violation ($\alpha = 0.025$) to determine the existence of any mean differences between age groups across levels of the EMMS factors. Additionally, Welch's and Brown-Forsythe *F* tests were used to determine significance as well (Tabachnick & Fidell, 2013). Table 17 displays the means and standard deviations for AGE on the EMMS factors.

The One-way Between-Subjects ANOVA tests yielded statistically significant mean differences between AGE and all EMMS factors, $F(5, 453) = 3.87$, $p < .0019$ [AUTOLE], $F(5, 453) = 4.60$, $p < .0002$ [COMATT], $F(4, 453) = 6.07$, $p < .0001$ [RELATE] and, $F(5, 453) = 2.84$, $p < .0155$ [LEARNS]. Additionally, the robust tests of equality of means supported the significance of the results given the violations of Levene's test of homogeneity of variances. Table 18 displays the *F* statistics for the between-subjects effects of (AGE) on each level of the EMMS factors.

Table 16: One-way ANOVA Tests of Between-Subjects Effects for COURSE

DV*	df_1	F	p
AUTOLE	3	0.91	0.44
COMATT	3	1.20	0.31
LEARNS	3	0.31	0.92
RELATE	3	1.76	0.16

Note. *DV= Dependent Variables. Significance level, $p < .025$ and error $df_2 = 218$.

Table 17: Means and Standard Deviations for Age

DV	Age	Mean	SD	N
AUTOLE	18 – 24	-0.14	0.94	309
	25 – 31	0.18	1.00	59
	32 – 38	0.22	0.84	34
	39 – 45	0.13	1.14	23
	46 – 52	0.57	0.57	23
	53 or over	0.14	1.25	11
COMATT	18 – 24	-0.14	0.98	309
	25 – 31	0.15	1.03	59
	32 – 38	0.23	0.70	34
	39 – 45	0.06	1.05	23
	46 – 52	0.61	0.60	23
	53 or over	0.54	0.59	11

Table 17 Continued

DV	Age	Mean	SD	N
LEARNS	18 – 24	-0.16	0.96	309
	25 – 31	0.14	0.95	59
	32 – 38	0.25	0.74	34
	39 – 45	0.34	0.68	23
	46 – 52	0.63	0.56	23
	53 or over	0.48	0.90	11
RELATE	18 – 24	-0.08	0.92	309
	25 – 31	0.04	0.96	59
	32 – 38	0.15	0.82	34
	39 – 45	0.00	1.12	23
	46 – 52	0.36	0.65	23
	53 or over	0.72	0.43	11

Table 18: Robust Tests of the Equality of Means for AGE

DV	Robust Test*	*F*	df_1	df_2	*p*
AUTOLE	Welch	6.38	5	54.49	0.000
	Brown-Forsythe	3.54	5	71.62	0.006
COMATT	Welch	7.86	5	56.85	0.000
	Brown-Forsythe	6.02	5	132.31	0.000
LEARNS	Welch	9.26	5	56.23	0.000
	Brown-Forsythe	8.13	5	103.72	0.000
RELATE	Welch	7.42	5	57.78	0.000
	Brown-Forsythe	3.36	5	122.03	0.007

Note. *Asymptotically *F* distributed, $p < 0.025$

Follow-up analyses were carried out using Bonferroni adjustments ($\alpha = 0.025$). Of all pairwise analyses between AGE on all EMMS factors, three yielded statistically significant results. These were all between the same two age groups; respondents 18 – 24 years of age and those 46 – 52 years of age on AUTOLE (mean difference [*MD*] = -0.70) and $p = 0.009$, COMATT (*MD* = -0.75) with $p = 0.005$, and RELATE (*MD* = -0.79) with $p = 0.001$. Results suggested that respondents ages 46 – 52 years old felt that the E-Model learning environment was more supportive of their individual autonomy, placed more value in using a CLS, and were more connected to the instructor/tutor in the learning environment than respondents 18 – 24 years of age. The effect sizes were large for both AUTOLE (*d* = 0.91) and COMATT (*d* = 0.92), while the effect size for RELATE was medium (*d* = .55) Given the significance of these results, AGE was used as an IV in the multiple regression analysis.

Standard multiple regression. Additional assumptions specific to multiple regression were addressed prior to analysis. These were multicollinearity of the IVs, homoscedasticity, and independence of residuals. Initially, bivariate correlations of the IVs were performed to determine whether any of the IVs needed to be removed. These results further supported the elimination of COURSE from the analysis as was suggested from the ANOVA results when comparing the different courses across levels of the EMMS factors. Course was highly correlated with college (*r* = -0.89; see Table 19). Visual inspection of the standardized residuals plots suggested only minor issue with homoscedasticity. There were no major concerns with violation of any assumptions. Independence of residuals was satisfied for all multiple regression analyses between the predictor variables (college and age) and the response variables (EMMS factors). All DW values were < 2.

Table 19: Bivariate Correlations Between Predictor Independent Variables (IV)

IV	College	Course	Age	Semester
College	1			
Course	-0.89** (n = 463)	1		
Age	0.50* (n = 459)	-0.45** (n = 459)	1	
Semester	0.19** (n = 435)	-0.20** (n = 435)	0.10* (n = 432)	1

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

Are college and age predictors of the EMMS factors (RQ5)? To assess this effect on the EMMS factors, four standard multiple regressions were performed. The size of this effect was measured by the amount of unique variance (sr_i^2) contributed by each predictor variable to the overall model given statistically significant results at the 0.05 level. Prior to analysis, AGE was recoded into indicator variables where the youngest age group (18 – 24) was used as the reference variable to determine the group(s) with statistically significant contributions on the respective DVs (EMMS factors). Notably, the youngest age group was initially recoded to be zero. The significant differences across three of the levels of the EMMS factors from the results of RQ3 was the reason for recoding the youngest age group as the reference variable to explore predictability by investigating differences between the youngest age group against the other age groups when analyzed simultaneously as a potential predictor of each level of the EMMS factors in separate analyses.

The first multiple regression analysis determined the effects on AUTOLE by the IVs. The overall multiple regression analysis indicated that the autonomy-supportive learning environment (AUTOLE) was impacted by college and age, $F(6, 456) = 4.07$, $p < .001$. The model was statistically significant from zero, R = 0.23 with Adj. $R^2 = .04$. Both college and age accounted for 4% (adjusted R^2) of the variation in AUTOLE. The unique contribution by college was statistically significant ($\beta = .13$, $sr_i^2 = .11$). In other words, AUTOLE was impacted by respondents from COLLA, which was an indication that these respondents felt that the E-Model design for course instruction was more supportive of their autonomy than those respondents from COLLB. Regarding AGE, respondents from age group 46 – 52 made a significant impact on AUTOLE ($\beta = .12$, $sr_i^2 = .11$) when compared with the 53 or over age group. A display of the weights and unique model contributions are in Table 20.

Table 20: Autonomy-supportive Learning Environment (AUTOLE) Effects

IV	B	β	Sig.	sr_i^2
College	0.25	0.13	0.019*	0.11
25-31	0.16	0.06	0.286	0.05
32-38	0.20	0.05	0.272	0.05
39-45	0.08	0.02	0.718	0.02
46-52	0.52	0.12	0.016*	0.11
53 or over	0.12	0.02	0.690	0.02

Note. R = .23 and Adj. R^2 = .04, (*N* = 459, *p* = .0001). Age group (18-24) = reference variable. $p < .05$*

The second multiple regression analysis determined the effects on COMATT by the IVs. The overall multiple regression analysis indicated that COMATT was also impacted by college and age, $F(6, 456) = 4.45$, $p < .0001$. The model was statistically significant from zero, R = 0.24 with Adj. $R^2 = .04$. Both college and age accounted for 4% (adjusted R^2) of the variation in COMATT. Respondents from COLLA significantly impacted COMATT ($\beta = .11$, $sr_i^2 = .09$). Consistent with previous result regarding AGE, respondents from the age group 46 – 52 significantly impacted COMATT ($\beta = .13$, $sr_i^2 = .12$). A display of these results are in Table 21.

A third multiple regression analysis determined the effects on RELATE by the IVs. The overall multiple regression analysis showed that RELATE was impacted by college and age, $F(6, 456) = 9.8$, $p < .0001$. The model was statistically significant from zero, R = 0.34 with Adj. $R^2 = .10$. Both college and age accounted for 10% (adjusted R^2) of the variation in RELATE. The unique contribution by college was statistically significant ($\beta = .29$, $sr_i^2 = .23$). In other words, RELATE was impacted by respondents from COLLA. Regarding AGE, respondents from the same age group 46 – 52 significantly impacted RELATE ($\beta = .13$, $sr_i^2 = .12$). These results are displayed in Table 22.

A final multiple regression analysis determined the effects on LEARNS by the IVs. The overall multiple regression analysis showed that LEARNS was impacted by college and age as well, $F(6, 456) = 4.22$, $p < .0001$. The model was statistically significant from zero, R = 0.23 with Adj. $R^2 = .04$. Both college and age accounted for 4% (adjusted R^2) of the variation in LEARNS. The unique contribution by college was statistically significant ($\beta = .19$, $sr_i^2 = .15$). In other words, LEARNS was impacted by respondents from COLLA as well. In contrast from previous results, respondents from age group 53 or over significantly impacted LEARNS ($\beta = .10$, $sr_i^2 = .10$). See Table 23 for specifics. Notably, only 5% of respondents from COLLB were

Table 21: Computer Attitude (COMATT) Effects

IV	B	β	Sig.	sr_i^2
College	0.22	0.11	0.042*	0.09
25-31	0.15	0.05	0.327	0.05
32-38	0.23	0.06	0.207	0.06
39-45	0.03	0.01	0.876	0.01
46-52	0.59	0.13	0.007*	0.12
53 or over	0.54	0.09	0.070	0.08

Note. $R = .24$ and Adj. $R^2 = .04$, ($N = 459$, $p = .0001$). Age group (18-24) = reference variable. $p < .05$*

Table 22: Relatedness to the Instructor/Tutor (RELATE) Effects

IV	B	β	Sig.	sr_i^2
College	0.54	0.29	0.000*	0.23
25-31	-0.02	-0.01	0.862	-0.01
32-38	0.09	0.02	0.613	0.02
39-45	0.13	0.03	0.524	0.03
46-52	0.41	0.10	0.045*	0.09
53 or over	0.32	0.05	0.258	0.05

Note. R = .23 and Adj. R^2 = .04, (*N* = 459, *p* = .0001). Age group (18-24) = reference variable. $p < .05$*

Table 23: Metacognitive Learning Strategies (LEARNS) Effects

IV	B	β	Sig.	sr_i^2
College	0.35	0.19	0.001*	0.15
25-31	-0.08	-0.03	0.571	-0.03
32-38	0.03	0.01	0.875	0.01
39-45	-0.15	-0.04	0.461	-0.03
46-52	0.21	0.05	0.323	0.05
53 or over	0.60	0.10	0.037*	0.10

Note. R = .23 and Adj. R^2 = .04, (*N* = 459, *p* = .0001). Age group (18-24) = reference variable. $p < .05$*

older than 24 years of age. Interestingly, no respondents from COLLB were from the age groups 39 – 45 and 46 – 52, which should be to no surprise that the results for COLLA were statistically significant in all multiple regression analyses.

Open-Response Item Analysis

There were two open-ended response items that allowed respondents to provide additional information or comments that provided more insight into the learning experiences of respondents in the E-Model environment. These were: "Please provide any additional information that would help us further understand your learning experiences in the E-Model learning environment.", which preceded the demographic information and a phrase, "Additional comments:", that followed. The researcher used a version of *context analysis* to code textual data to identify themes (Popping, 2015). The goal was to identify emergent themes that were insightful and added to the interpretation of the research questions. Additional information about the demographic nature of the data included gender, age, ethnicity, college, and semester.

Overall open-response demographics. There were n = 163 total comments provided by respondents. Female respondents (71.8%, n = 117) provided more comments than male respondents (27%, n = 44). More comments were from younger respondents (18 – 24, 67.5%, n = 110) and (25 – 31, 11%, n = 18) with an equal number of comments from the age groups 39 – 45 and 46 – 52 (6.1%, n = 10) and less than 5% from the other age groups. There was at least one comment from all ethnic groups except the Native Hawaiian or Other Pacific Islander with a majority of the comments from White respondents (62.6%, n = 102). There was a fair representation from the minority groups (Hispanic or Latino [14.7%, n = 24], Black or African American [9.2%, n = 15] and Asian [4.9%, n = 8]). Many of the comments were from respondents who completed their coursework in the first semester (65%, n = 106). At least 20%

of the comments were from respondents who needed two or more semesters to complete coursework. The comments were nearly evenly split between the two colleges (COLLA: 49.7%, *n* = 81 and COLLB: 50.3%, *n* = 82). Table 24 is a display of these demographics.

When considering demographic information by college, the female to male ratio was approximately the same (COLLA: 2.5 and COLLB: 2.8). In terms of age, more comments were from younger respondents (18 – 24) from COLLB (95.1%, *n* = 78) while there was more representation across age groups for COLLA with at least 59.2% of the comments from respondents older than 24 years of age. In terms of ethnicity, there were more comments from White respondents who were from COLLA (75.3%, *n* = 61) while the comments from COLLB were evenly split amongst White and non-White respondents. Lastly, the ratio of respondents who provided comments and needed two or more semesters to complete coursework from COLLA was 2.1 time more than from COLLB (see Table 25).

Open-response item analysis procedure. The researcher read through the comments twice. The first review allowed the researcher to process the information to begin thinking about themes as well as make notes. Following the first read, it was apparent that there were three types of comments. Comments were either negative, positive, or those that suggested improvements or eluded to some type of change. Furthermore, negative comments were directed at specific aspects of the E-Model learning experience that potentially disrupted students' BPNS (e.g., not liking the CLS, not connecting with the instructor/tutor or hated taking quizzes in the lab). After strategizing, the researcher finalized the emergent themes and assigned a unique code to items during the second read. For specific quotes, a few minor changes were made that were related to grammar and punctuation (e.g., adding a comma, a period, or changing misspelled

Table 24: Overall Open-Response Items Demographics

Variable	Sample Size (n)	Percentage (%)
Gender		
Female	114	71.8
Male	44	27
Age		
18 – 24	110	67.5
25 – 31	18	11.0
32 – 38	5	3.1
39 – 45	10	6.1
46 – 52	10	6.1
53 or over	8	4.9
Ethnicity		
American Indian/Alaska Native	1	0.6
Asian	8	4.9
Black/African American	15	9.2

Table 24 Continued

Variable	Sample Size (n)	Percentage (%)
Hispanic/Latino	24	14.7
Native Hawaiian/Other Pacific Islander	0	0.0
Other	6	3.7
White	102	62.6
College		
COLLA	81	49.7
COLLB	82	50.3
Semester		
1 semester	106	65.0
2 semesters	20	12.3
3 or more semesters	26	16.0

Table 25: Open-Response Items Demographics by College

	COLLA		COLLB	
Variable	(*n*)	(%)	(*n*)	(%)
Gender				
Female	58	71.6	59	72.0
Male	23	28.4	21	25.6
Age				
18 – 24	32	39.5	78	95.1
25 – 31	16	19.8	2	2.4
32 – 38	5	6.2	0	0.0
39 – 45	10	12.3	0	0.0
46 – 52	10	12.3	0	0.0
53 or over	7	8.6	1	1.2
Ethnicity				
American Indian	1	1.2	0	0.0
Asian	2	2.5	6	7.3

Table 25 Continued

Variable	COLLA (*n*)	COLLA (%)	COLLB (*n*)	COLLB (%)
Black	5	6.2	10	12.2
Hispanic	3	3.7	21	25.6
Other	3	3.7	3	3.7
White	61	75.3	41	50.0
Semester				
1Semester	43	53.1	63	76.8
2 Semesters	13	16.0	7	8.5
3 or more semesters	18	22.2	8	9.8

words to the correct spelling). Table 26 lists the themes, assigned code, and description or rationale used.

Open-response attitudinal results. There were 2.2 times as many positive comments (58.9%, n = 96) than negative comments (27.0%, n = 44) while the rest of the comments suggested needs for improvement or a notion of change (14.1%, n = 23). Females respondents provided more positive and negative comments than male respondents. The positive to negative ratio of female comments was 2.7. The same ratio for males was 1.4. Hence, females provided more positive comments expressing their learning experiences in the E-Model environment than male respondents (see Table 27). Notably, more female and male respondents expressed enjoyment of their experience and indicated that the experience overall was great. These respondents expressed the potential intrinsic nature of learning in the E-Model environment. For example, one female respondent stated:

> " I don't think I would have learned as much as I've learned thus far. Although I have failed the module I'm on in the past, I have confidence in learning the material because of the E-Model Learning environment. Had it not been for this type of environment, I may have given up on learning this module and quit college all together. Math has always been a difficult subject for me which is why I've waited so many years before attending college."

One male respondent highlighted a similar experience that captured the essence of learning in an E-Model environment (i.e., expressing the potential to become an independent learner and self-assessor) by stating:

"I liked that each module was broken down into sections and allowed us to master a concept before moving on to the next one. I liked the "help me solve this" feature that

Table 26: Description of Emergent Themes and Assigned Code Values

Themes	Descriptions
Negative Attitude = 0	Comments that indicated a dislike for any aspect of the E-Model learning experience. For example, COLLA: "*I did not like this at all, was a terrible way to teach and try to understand math*." or COLLB: "*I did not enjoy learning from the E-model. You have access to the internet and in most cases if we couldn't figure out the problem we consulted the internet.*"

Table 26 Continued

Themes	Descriptions
Positive Attitude = 1	Comments that indicated praise of any aspect of the E-Model learning experience. For example, COLLA: "*I thought it was a very helpful way to learn and let me do it at my own pace.*" COLLB: "*I much preferred the E-Model over the traditional way of learning mathematics!*"

Table 26 Continued

Themes	Descriptions
Improvement = 2	Comments that were neither negative nor positive but suggested a need for improvement or general statement eluding to change. For example, COLLA: "*Attendance should only be required for taking tests and quizzes*." or COLLB: "*More tutors in the lab would be helpful to the students*."
BPNS*	
Support = 0	All positive comments.

Table 26 Continued

Themes	Descriptions
Impeding Autonomy = 1	Negative comments that suggested general autonomy was affected or eluded to competence or relatedness as disruptors of BPNS. For example, COLLA: "*I did not like learning math this way. I liked the self-pace when it came to stuff I was familiar with, but with more advanced math it was a nightmare. It was no fun trying to teach myself something I did not know*." or COLLB: "*The E-Model learning environment was terrible. Not only was I told different things by my professor, textbook, and computer software, but I also was told something different by every individual tutor in the lab*."
Impeding Competence = 2	Comments that were negative and suggested competence as potential disruptor. Examples were only from COLLA (e.g., "*E-Model isn't for everyone and I personally struggled. Not because the material was hard but because I limited myself and did not have the confidence I had when I first enrolled*.").

Table 26 Continued

Themes	Descriptions
Impeding Relatedness = 3	Comments that were negative and suggested relatedness as potential disruptor. For example, COLLA: "*Usually the staff in the lab that I had to take those courses in looked bored or irritated to be there. I wasn't inclined to ask them questions because it looked like a chore when I still didn't understand something. Sometimes I'd need more explanation and the online course and lab instructor still left me confused, wondering what exactly I needed to do.*". or COLLB: "*In the E-mod learning environment I had a tutor say, "You don't know how to do this?" Then I said no, and he just told me the answer, which doesn't help at all.*".

*Note. *All comments labeled as improvement were further analyzed and were placed in one of the four subgroups. The researcher also referred to respondents' closed-ended responses when it was not clear in which subgroup the comment should be placed.*

Table 27: Results of Attitudes Across Demographics and BPNS Impediment

Variable	Attitude		
	N(%)	P(%)	NI(%)
Gender			
Female	36.0	22.9	26.1
Male	61.4	76.0	73.9
Age			
18 – 24	70.5	64.6	73.9
25 – 31	15.9	9.4	8.7
32 – 38	4.5	3.1	0
39 – 45	6.8	5.2	8.7
46 – 52	0	9.4	4.3
53 – 59	2.3	6.3	4.3
Ethnicity			
American Indian/ Alaska Native	0.0	0.0	4.3
Asian	0.0	8.3	0.0

Table 27 Continued

	Attitude		
Variable	N(%)	P(%)	NI(%)
Black/African American	0.0	12.5	13.0
Hispanic/Latino	11.9	14.6	21.7
Other	4.5	3.1	4.3
White	77.3	58.3	52.2
College			
COLLA	59.1	50.0	30.4
COLLB	40.9	50.0	69.6
Semester			
1 semester	47.7	71.9	69.9
2 semesters	22.7	8.3	8.7
3 or more semesters	18.2	14.6	17.4
BPNS			
Support	0.0	96.9	78.3
Impeding Autonomy	81.8	3.1	21.7

Table 27 Continued

	Attitude		
Variable	N(%)	P(%)	NI(%)
Impeding Competence	4.5	0.0	0.0
Impeding Relatedness	13.6	0.0	0.0
Totals	*n* = 44	*n* = 96	*n* = 23

Note. **N** = Negative, **P** = Positive, and **NI** = Needs Improvement.

allowed me to see the steps of how to solve the problems I was struggling with. I appreciated the opportunity to do practice problems and homework for each module which allowed me to judge if I was ready to take the test. The instructors and tutors on campus are a great resource to assist us and answer any questions. I enjoy module math and the instructors and have gained more knowledge in math because of the learning model."

While these examples were representative of the many types of positive interactions experienced by respondents in the E-Model environment, there were instances where respondents expressed their frustrations with the learning approach. For example, one female respondent stated:

> "I did not like the modules. I thought they were hard. Mainly because learning a subject online is not my learning style. I prefer a face to face class were the teacher teaches you, not a computer. Also, the modules were very frustrating to say the least."

Similar frustrations were expressed by a male respondent who stated:

> "I'm the type of student that likes learning math from an actual instructor. It easily frustrated me because I knew going into a module that I didn't understand it. The pretests we take before the module are major downers. After seeing a 36% on a test you really aren't too motivated to continue."

Negative experiences such as these and those listed in Table 26 were examples representing how students' overall BPNS can be hindered by learning in the E-Model environment that might not have been autonomy-supportive for all students.

Further analysis revealed that an overwhelming majority of comments were from younger respondents in the age range 18 – 24 years old. Comments were twice as positive than negative with this age group overall. When compared with the ratio of positive to negative respondents older than 38 years of age, older respondents were 5.8 times more positive in their expression of their experiences than negative overall. However, more respondents from the 18 – 24 age group (73.9%) indicated a need for improvement or eluded to some form of change.

There were interesting findings when analyzing ethnicity by attitude. Approximately 77% of negative comments were from White respondents, 11.4% from Hispanic/Latino respondents, and 4.5% were in the ethnic group Other. There were no negative comments from the Asian or Black/African American respondents. Of all 94 positive comments, 8.3% were from Asian respondents, 12.5% were from Black/African American respondents, 14.6% were from Hispanic/Latino respondents and 58.3% were from White respondents. Although White respondents provided more positive comments, when comparing the ratios of positive to negative comments across the ethnic groups, their ratio was the smallest (1.6). Black/African American respondents had the largest ratio (12), then Asian respondents (8), followed by Hispanic/Latino respondents (2.8). These results suggested Black/African American respondents who commented, were more positively receptive of the E-Model environment. Of the 23 needs improvement comments, over half (52.2%) were from White respondents, 21.7% from Hispanic/Latino, 13% from Black/African American respondents. These respondents expressed a variety of needs improvement. These were: better quality videos, more lab space, stop making it mandatory, provide incentives, or slightly noisy at times.

When considering semester by attitude, at least 47% of comments were from respondents who completed their coursework in the first semester. Interestingly, respondents who needed more than three semesters to complete their coursework provided 1.8 times as many positive comments than negative comments. Having to repeat or needing more time to complete all coursework can be challenging and frustrating for students. One respondent in particular stated the following:

> "I have spent more time teaching myself this material than if I had access to a regular, traditional course. It is frustrating and discouraging to me."

On the other hand, respondents seemed to welcome the challenge and enjoyed the experience stating:

"The professors were always professional and encouraging towards my college goals. I always used additional resources for clarity and understanding of the course work at hand. I have always struggled with mathematics. eLearning has allowed for better clarity and memorization of the course material."

The impeding BPNS results (Table 27) provided additional information regarding the challenges faced by approximately 27% of respondents who provided negative comments and were willing to further expound on their experiences in the E-Model environment, out of n = 163 responses. Results revealed that a majority of the respondents (81.8%, n = 36) who provided negative comments, felt less autonomous in the E-Model environment. Their comments suggested that they were less confident (4.5%), had an unpleasant experience with the instructor/tutor (13.6%), or were so frustrated with other aspects of the E-Model learning experience that it affected overall autonomy.

The comparison of college data by attitude revealed there were more negative comments from respondents who were from COLLA (59.1%, n = 26) than COLLB (40.9%, n = 18). There were an equal number of positive comments from both colleges. However, respondents from COLLB (69.6%, n = 16) provided over twice as many needs improvement comments than COLLA (30.4%, n = 7), given there were n = 23 total comments.

As discussed in Chapter 2, students had the best opportunity to thrive and grow when they were in an environment that was autonomy-supportive, provided the opportunity to build competence, and had a sense of relatedness to the environment. The comments provided in this research study were informative. The comments either expressed the intrinsic nature of learning in the E-Model environment or signaled apprise indicating how a learning environment, that was designed for the more autonomous learner, can impede an individuals' ability to succeed in the E-Model learning environment. In closing, when considering the total number of respondents who participated in the research study (*n* = 463), the negative comments accounted for approximately 9% of overall responses. When considering these negative comments by college, COLLA accounted for approximately 11% of these comments and COLLB approximately 8%.

CHAPTER 5: DISCUSSION

Summary of Findings

The purpose of the study was to develop and begin the validation process of a survey instrument designed to learn more about students' motivations learning in a non-traditional learning environment; the E-Model design for course instruction. Additionally, the goal was to determine whether learning in a course designed using the E-Model was supportive of students' BPNS; a learning environment that provided students the opportunity to become more self-directed, confident in their abilities to perform, and feel a connected to the learning environment. The following hypotheses and research questions were developed to fulfill the purpose of the current research study.

Hypotheses:

1. The Emporium Model Motivation Scale would yield parsimonious factor solutions and be a valid measure of autonomous motivation (*H1*).
2. The Emporium Model Motivation Scale would yield satisfactory internal consistency reliability of factor solutions using Ordinal Omega Coefficient $\alpha \geq .70$ (*H2*).

Research questions:

1. Are there differences in college on the EMMS factors (RQ1)?
2. Are there differences in course (Intermediate Algebra, College Algebra, Finite Mathematics, and Pre-Calculus) on the EMMS factors (RQ2)?
3. Are there differences in age on the EMMS factors (RQ3)?
4. Are there differences in semester on the EMMS factors (RQ4)?
5. Are college, course, and age, and semester predictors of the EMMS factors (RQ5)?

H1. The first hypothesis was to assess the internal structure of the EMMS initial 44-item and to determine whether the EMMS was a measure of higher levels of autonomy through convergent validity. The initial 44 items were factor analyzed using polychoric correlations as a result of fairly asymmetric data using Oblique methods to extract (ULS) and rotate (Promax) the potential factors. The researcher relied upon four methods to help determine the number of factors to retain. The reason for relying upon multiple methods was due to the fact that neither method was faultless (Osborne, 2014). The methods used were these: Kaiser's criterion (recommended 4 factors), Velicer's MAP (recommended 3 factors), Horn's PA (recommended 3 factors), and Schwarz BIC dimensionality test (recommended 3). The differences between the number of factors to retain from the given methods were due to the fact that specific variables in the data were highly correlated but not high enough (>. 90; Tabachnick & Fidell, 2013) to suggest removal. Table 11 displays the statistically significant bivariate correlations ($p < .01$) that includes the highly correlated EMMS factors (AUTOLE with COMATT and RELATE) with variables that were potentially highly correlated and contributed to the variation in the number of appropriate factors to retain amongst the different methods and could have influence the suggestion to retain a 3-factor solution using polychoric correlation. Hence, the recommendation to use more than one method (Osborne, 2014).

The EFA analysis led to four parsimonious factor solutions. These were: autonomy-supportive learning environment (AUTOLE), relatedness (RELATE), computer attitude (COMATT), and metacognitive learning strategies (LEARNS). The subscale AUTOLE consisted of 17 items measuring levels of autonomy in relation to the E-Model environment. The subscale RELATE consisted of 4 items measuring the relatability of the instructor/tutor in the E-Model environment. The subscale COMATT consisted of 5 items measuring the extent to which an individual valued the use of a CLS in the E-Model environment. The subscale LEARNS consisted of 6 items measuring the extent to which an individual relied on using metacognitive learning strategy in the E-Model environment. These 4 factors defined the EMMS consisting of 32 items.

Assessing convergent validity. Convergent validity was used to assess whether the EMMS factors were a valid measure of higher levels of autonomy. The Academic Motivation Scale (AMS) was used to complete this analysis by running bivariate correlations between the EMMS factors and AMS. The only factor that was positively, statistically, and significantly correlated with the AMS was the RELATE factor, which was considered a small effect (Cohen, 1992). Results of this analysis were an indication that the factors of the EMMS were not measuring higher levels of autonomy, which were debatable.

The outcome of the correlational analysis could have been related to whether the factors were domain specific (CSDT, 2019). All EMMS factors were designed to be domain specific: learning mathematics in the E-Model environment. The four items of the AMS were not specific to the domain in question. The AMS 4-factor subscale measured the extent to which an item corresponded to the respondents regarding the reason why they go to college and not the extent to which the items corresponded to the respondents in relation to their learning experiences in the E-Model environment.

Theoretically, the items of COMATT assessed the extent to which respondents valued the usefulness of the CLS in the E-Model environment and was found to be representative of identified regulation with a “locus of causality” that was “somewhat” internal with a regulatory process defined as “conscious valuing” or was a measure of “personal importance” (Legault, 2017; Ryan & Deci, 2000). Furthermore, several studies supported the validity and reliability of the COMATT factor to be a measure of identified regulation (Deci et al., 1994; McAuley et al., 1989; Ryan, 1982; Schuttle et al., 2017). The COMATT subscale could have been used to satisfy convergent validity, which was positively, statistically, and significantly correlated with all other subscale factors of the EMMS with medium to large effect sizes (Cohen, 1992). In this case, the AMS was not the best subscale to assess the autonomous nature of the EMMS factors even though the subscale had been shown to be positively, statistically, and significantly correlated to autonomy-supportive traits; suggesting it was a measure of identified regulation (Vallerand, et al., 1993). However, any meaningful interpretation of the relationship between the two factors could have suggested that the "conscious valuing" respondents placed on the reasons why they go to college, expressed higher levels of autonomy (with regard to identified regulation) than the "conscious valuing" respondents placed on their learning experiences in the E-Model environment.

H2. The internal consistency of the reliability of the items were to be determined based on the Ordinal Omega Coefficient Alpha $\omega \geq 0.70$. All reliability coefficients exceeded the minimum criterion with precise 95% CIs, further strengthening the reliability to be replicable across studies. The reliability for AUTOLE was $\omega = 0.98$ with 95% CI (0.97, 0.98). The reliability for RELATE was $\omega = 0.91$ with 95% CI (0.90, 0.92). The reliability for COMATT was $\omega = 0.96$ with 95% CI (0.96, 0.997). And, the reliability for LEARNS was $\omega = 0.89$ with 95% CI (0.88, 0.91).

Assessing factor score estimates and replicability. To provide additional support for the validity of the EMMS factors to be replicable across studies or the potential to be generalizable was determined using the *Generalized H* (G-H) indices (Ferrando & Lorenzo-Seva, 2017a). Both the *G-H Observed* and *Latent* indices met the minimum criterion of > 0.80 for each of the EMMS factors and ranged from 0.92 – 0.98 for the *H*-Latent indices and ranged from 0.85 – 0.92 for the *H*-Observed indices. These indices were supported with 95% CIs ranging from a low of 0.65 – 0.98. These results made a strong case for generalizability of the EMMS.

Additional indices assessed the indeterminacy of the factor score estimates (*factor determinacy index* [FDI > .90]) as well as provided *marginal reliabilities* (MR > .90) to determine the accuracy of the estimates to be a representation of the true factor score (Ferrando & Lorenzo-Seva, 2016). The standardized factor score estimates for each of the EMMS factors were determined to be accurate and reliable scores for each of the EMMS factors with FDI indices ranging from 0.98 – 0.99 and MR indices ranging from 0.92 – 0.98.

Assessing the research questions. Five research questions were constructed to provide additional information to support the validity of the EMMS items by analyzing mean differences between specific IVs (college, course, age, and semester) on the EMMS factors. This was completed by performing a One-way Between-Subjects MANOVA and single-level ANOVAs. Additional Standard Multiple Regression analyses were performed using IVs that produced statistically significant results from investigations of mean differences to determine any statistically significant unique contributions by the IVs on each of the EMMS factors in separate analyses.

RQ1. Results from a One-way MANOVA comparing mean differences between respondents at a community college (COLLA) and respondents at a public university (COLLB) on the EMMS factors were overall statistically significant following assumption testing. Follow-up single level ANOVAs identified specifically where the differences occurred. All results were statistically significant on the EMMs factors. Results revealed that respondents from COLLA agreed that the E-Model environment was more supportive of their overall autonomy than

COLLB respondents. COLLA respondents believed that the instructors/tutors in the E-Model environment were more relatable than COLLB respondents. They placed more value on using a computer learning system than COLLB respondents. And, COLLA respondents were more likely to utilize metacognitive learning strategies in the E-Model environment than COLLB respondents. Notably, the demographic information revealed that an overwhelming majority (98%) of respondents older than 39 years of age were from COLLA. These findings were consistent with those in autonomy research suggesting that autonomy increased with age (Sheldon, & Kasser, 2001).

RQ2. Four One-way Between-Subjects ANOVA tests were used to analyze mean differences between four mathematics gateway courses (*Intermediate Algebra, College Algebra, Finite Mathematics, and Pre-Calculus*) taken by respondents at COLLB on the EMMS factors. Box's *M* test was significant for all IVs on the EMMS factors. Levene's test, however, was significant for all IVs on the EMMS factors except LEARNS. Tests of the robustness of mean differences were used (Welch's and Brown-Forsythe's *F* tests) given that the tests were robust to violations of Levene's test of homogeneity of variances (Tomarken & Serlin, 1986). To be more cautious, a more stringent alpha ($\alpha = 0.025$) was used (Tabachnick & Fidell, 2013). Results were found to be non-significant for all mean differences between the courses on the EMMS factors. Results suggested that respondents in the current research study who took one of the college level gateway courses had similar levels of motivational experiences in the E-Model environment related to learning environment autonomy, relatability, the importance of using a CLS and the use of metacognitive learning strategies.

RQ3. Four One-way Between-Subjects ANOVA tests were used the determine means difference between age groups on the EMMS factors for reasons similar to analyses conducted in

RQ2 regarding assumptions. Four robust tests of mean differences yielded statistically significant results with $\alpha < 0.025$ for each of the EMMS factors. Follow-up Bonferroni adjustments were run to identify specific differences between the age groups on the EMMS factors using a more stringent alpha ($\alpha = 0.025$). Results revealed three statistically significant mean differences (MD) between two age groups (18 – 24) and (46 – 52) on three of the EMMS factors (AUTOLE [*MD* = -0.70], COMATT [*MD* = -0.75], and RELATE [*MD* = -0.79). The negative MD favored respondents who were ages 46 – 52 years old. These results were an explanation of the statistically significant outcomes between COLLA and COLLB. These results further supported the case that the desire to strive for autonomy increased with age which also strengthened the argument that the E-Model was better suited for the more self-determined (Williams, 2016).

RQ4. Addressing issues of assumption testing led to the removal of RQ4 from the analysis. RQ4 was to examine the mean differences between the number of semesters it took for respondents to complete their coursework across levels of the EMMS factors. Bivariate correlational analysis between the EMMS factors (DVs) and specific demographic variables (IVs) were all statistically significant at the 0.05 level except for the correlations between the EMMS factors and SEMESTER, which derived very low correlational values (r = -0.04 to 0.07).

RQ5. Four Standard Multiple Regression analyses were performed to determine any statistically significant effects on the EMMS factors separately with respects to COLLEGE and AGE following satisfactory assumption testing. Each of the four multiple regression analyses revealed statistically significant overall results at the 0.05 level of significance. All EMMS factors were affected by COLLEGE and AGE. In each of the four multiple regression analyses, respondents from COLLA had more of an effect on each of the EMMS factors with unique contributions represented by squared partial correlations (sr^2). These were: AUTOLE (β = .15, sr_i^2 = .13), COMATT (β = .11, sr_i^2 = .09), RELATE (β = .29, sr_i^2 = .23), and LEARNS (β = .19, sr_i^2 = .15). Additionally, results suggested that respondents from COLLA had more of an effect on the RELATE factor.

When considering the effects that AGE had on each of the EMMS factors, multiple regression analyses revealed that respondents who were ages (46 – 52) made a significant impact on AUTOLE (β = .52, sr_i^2 = .12), COMATT (β = .13, sr_i^2 = .12), and RELATE (β = .13, sr_i^2 = .12) when compared with the reference group (18 – 24). Only respondents who were ages (53 or over) made a significant impact on LEARNS (β = .19, sr_i^2 = .15) when compared with the reference group as well. These results suggested that AGE contributed approximately the same amount of unique variance on all EMMS factors. However, the effect sizes for practical significance of these results were small with Cohens f^2 values ranging between 0.04 – 0.11 (Cohen, 1992).

Limitations

There were few limitations worth mentioning. The researcher expected to achieve a response rate of at least 10%. However, after cleaning the data approximately 8%, n = 463 were used in subsequent analysis. While the response rate was not greater than 10%, it was large enough to be 95% confident in the responses from respondents (CheckMark, 2019). There were slight violations of both the normality and linearity assumptions. However, linearity techniques were robust to violation of the normality assumption so as long as the data were not severely skewed (Garson, 2012). This was not the case for the data in the current study. Rather than delete outliers, data were winsorized to ± 3 standard deviations from the mean. Winsorizing had the potential to biased results when trimmed closer to the mean and not addressing the issue of outliers could have altered the outcome if left alone (Garson, 2012).

It was clearly obvious that the sample sizes were unequal. Other limitations resulted from the violation of Box's *M* test of homogeneity of variance-covariance matrices and Levene's tests of homogeneity of variances for both course and age, which resulted in running single level Between-Subjects ANOVAs. To address this issue, the researcher relied on the robust test of mean differences given it was robust to violations of the Levene's test of homogeneity of variances (Tomarken & Serlin, 1986). Although quantitative analyses did not include gender as an IV, the target population overwhelmingly consisted of White female respondents. This lack of gender and ethnic diversity could affect generalizability of results. Based on these limitations, results should be interpreted with caution.

Implications

The exploratory phase of the validation process exceeded the recommended threshold for measuring the internal structure of the EMMS and produced four highly reliable factor solutions. These results suggested that the E-Model design for course instruction was supportive of students' BPNS. In other words, the E-Model learning environment was autonomy-supportive. The environment positively influenced students perceptions of learning mathematics. Respondents were able to build confidence in their abilities and were able to establish a connect with the instructor/tutor in the E-Model environment. An indication of these claims were reflected in the moderate to high bivariate correlations between the EMMS factors as well as in the responses to each item of the factors.

Based on these results, the EMMS could be used in several ways. The instrument could be used as a mid-semester assessment tool to determine whether there were disruptions of students' BPNS. Results will allow appropriate personnel to provide any needed autonomy-support (i.e., *emotional support* or *instrumental support*; Federici & Skaalvik, 2014). Emotional support can come in several forms that reflect emotion (e.g., caring or empathizing, gaining trust or showing respect expressed through communication; Patrick, Kaplan, & Ryan, 2011). Providing students with this type of support is tactile and related to forms of instruction (e.g., explaining a mathematical concept, modeling a problem, or inquiry; Federici & Skaalvik, 2014) or assistance with the CLS given its central significance to the E-Model design.

Moreover, the EMMS could be used as part of a more holistic evaluation of courses or programs designed using the E-Model for course instruction. Rather than only assessing impact from completion rates and performance data, including an assessment of students' psychological dispositions with respects to learning in the E-Model environment, is more representative of a holistic approach (Bonham & Boylan, 2012; Liaw, 2012). Assessment of students' psychological dispositions had significance in that positive students' perceptions of their performance influenced engagement and outcome (Gagne, 2003).

Additionally, results may reveal a need for professional development training for faculty utilizing the E-Model. Training geared towards understanding more about learning theories, particularly SDT, which allows one to understand why it is important to promote an autonomy-supportive E-Model environment. Regardless of whether the training is geared towards faculty at a community college or 4-year college or university, the main goal is to inform these individuals about ways to support students' individual autonomy in light of implementation of the SOEs at the respective institutions of higher learning.

Naturally, students between the ages of 18 – 24 are going to be less autonomous at the beginning of their college experiences. Research suggests that students became more autonomous during their first 4 years of college (Wachs & Cooper, 2002), while other research suggests students will become more autonomously-natured when they separate from reliance on their parents and assume more adult related responsibilities (Cullaty, 2011). In an autonomous learning environment, students assume more ownership for their learning. When the less autonomous students receive support emotionally or instrumentally and utilize necessary skills to succeed (e.g., using metacognitive learning strategies), it allows for a smoother transition into becoming a more autonomous or self-directed learner (Cho & Heron, 2015; Federici & Skaalvik, 2014).

At the root of SDT is the assertion that we naturally seek autonomy, which means it is ongoing until events in our social environments disrupt this natural progression (Ryan & Deci, 2000; 2017). Therefore, the success of students' transition into becoming more autonomous or self-directed depends on the effectiveness of the support received. Professional development training is one way to provide faculty, tutors, or mentors resources to support students' BPNS. The use of the EMMS, in conjunction with a few qualitative items, may reveal a need to improve certain implementation aspects of the E-Model regarding the quality of available resources, means for monitoring noise levels, making changes to policies and guidelines or relatedness issues to support sustainability of the E-Model design to be autonomy-supportive. A few of these qualitative items could be:

- Reflecting on your experiences in the E-Model environment, what are some suggestions for improvement?
- Reflecting on your interactions with the instructors/tutors, how would you describe their behavior towards you?

- Reflecting on your experiences in the E-Model environment, what learning strategies did you use to help you succeed in the course?
- Please provide any additional information that would help us further understand your learning experiences in the E-Model learning environment.

Future Research

The EMMS was the only survey instrument developed using a theoretical framework rooted in SDT designed specifically to assess the autonomy-supportive nature of the E-Model environment. Therefore, continuing the validation process of the EMMS through Confirmatory Factor Analysis (CFA) is a necessary next step (DeVellis, 2012). Completing this process will be important future research in that valid and reliable results could be replicable across other samples and be generalizable to other populations. Moreover, findings of the current research study have produced indicators suggesting the possibility of generalizability. Future research should re-evaluate convergent validity using a subscale that was more domain specific. The *Intrinsic Motivation Inventory* (IMI; Ryan, 1982) and the *Basic Psychological Need Satisfaction* scale (BPNS; CSDT, 2019) contained other more appropriate subscales that could be used to assess whether the EMMS factors were a valid measure of autonomous motivation as defined by Ryan and Deci (2000).

Future research should include the analysis of secondary data (e.g., pre/post-test scores, GPA, success rates, or scores on college entrance exams etc.). The goal would be to learn more about the predictability nature of the EMMS factors on mathematics performance. Additional research should examine whether there existed an association between students' perceptions of learning mathematics in the E-Model environment and their perceptions of mathematics in general. It would be interesting to learn more about whether a more autonomy-supportive learning environment was predictive of mathematics learning and the affect this would have on students' BPNS.

Conclusions

The theoretical framework of the current research study was rooted in SDT, which asserted that all individuals strived for "autonomy, competence, and relatedness" in their social environments (Ryan & Deci, 2000; 2017). In other words, in order to have an aspiration for success, certain psychological aspects for well-being had to be satisfied (i.e., BPNS). When relating this theory to the learning environment, it suggested that students must have the right mindset and receive autonomy-support in order to take advantage of the opportunity to learn in the E-Model environment.

Results of the current research study have shown that the EMMS can be used to assess the autonomous nature of the E-Model environment through assessing the validity and reliability of the items of the EMMS, which derived four parsimonious factor solutions that measured higher levels of autonomy. Further analyses suggested that the E-Model environment was designed for the more autonomous learner and could be used to set the less autonomous learners on a path to becoming more autonomously-natured. Results also revealed that when students received the necessary autonomy-support from the instructor/tutor (whether emotional or instrumental) it provided the best opportunity for students to build confidence in their abilities to be successful in the E-Model learning environment. When the E-Model learning environment was autonomy-supportive it supported students' BPNS, which gave them the opportunity to thrive in the E-Model learning environment; the essence of SDT.

Current results were aligned with research suggesting the E-Model learning environment was better suited to be autonomy-supportive, which provided students the chance to build confidence and connect to the learning environment (Brey & Tangney, 2017; William, 2016) and promoted positive outcomes (Gagne, 2003). The comments from the open-response item analysis supported these claims. Overall, more students than not had a positive learning experience and believed that the E-Model environment helped them be more confident in their abilities and help them become more self-determined. These were outcomes consistent with other research studies that examined how learning in the E-Model environment positively impacted students' motivation and performance (Eckhardt, 2016; Komarraju & Nadler, 2013). Respondents also indicated how the E-Model environment helped them gain confidence in their abilities to learn mathematics. For example, one student stated: "… As someone who has always struggled with math, this was amazing. It really changed my opinion on math in general." Statements similar to these, that were made, reflected the idea that positive learning experiences in the E-Model environment influenced students' mindset and performance in mathematics (Eckhardt, 2016).

The literature review discussed in great detail the E-Model design and the 10 essential elements of the design that were divided into two component parts. These were the Core Structural Elements (CSEs) and the Strategic Operational Elements (SOEs). The CSEs were the core components of the E-Model design that were the structural foundations of the E-Model and common to all redesigns. The SOEs were related to the interactions within the learning environment that potentially disrupted the learning process and impeded students' BPNS given issues with implementation. The sample of open-response comments from Table 26 were examples that represented issues with implementation of the SOEs from both the community college and public university. The number one complaint by respondents was being forced to stay in the lab to complete quizzes at the university. Others included better qualified tutors, better quality videos, and comments related to noise in the lab as well as issues with the instructor/tutor from both institutions of higher learning.

On the other hand, comments revealed another potential need regarding the addition of a new CSE component (i.e., The E-Model learning environment should be structured to support students BPNS). The negative comments provided by respondents from both colleges centered around their dislike for the E-Model approach due to the fact that they had to be actively-engaged in learning that involved them having to teach themselves. Many respondents did not like that they had to teach themselves the material or indicated that they preferred to be in the traditional classroom where “the teacher teaches you”, according to one respondent. Statements similar to the ones highlighted in the current research study, in addition to the impeding BPNS themes in Table 26, were examples reflecting the frustrations of respondents that might have influenced their dislike for the E-Model approach. These results suggested an issue with messaging or communication of the purpose for learning in a more student-centered environment that could be “…great for people that know how to pace themselves and enjoy learning on their own”, as one respondent stated. This quote reflected the contrast between the respondents who provided the positive comments and those who provided the negative comments. Respondents who provided the negative comments were not as self-directed as those who provided positive comments and possibly suggested that these respondents were infrequent users of metacognitive learning strategies. Or, comments similar to the ones referenced here could be signaling a need for professional development for the instructors and tutors who will most likely interact with students in the E-Model environment.

As previously pointed out in the review of literature, more research studies focused on measuring the impact of learning in the E-Model environment compared to learning in the TI environment with less emphasis on the effectiveness of the E-Model environment relative to an assessment of students' psychological well-being. The results were clear and growing, that students who took courses using the E-Model design for course instruction tended to out-perform students who took a course using the TI approach at institutions of higher learning (Cousins-Cooper et. al., 2017; Eckhart, 2015; Krupa et al., 2015; Vallade 2013). The mission moving forward should include additional research focused on the psychological impact faced by students learning in an environment that was designed for the more autonomous and self-directed learner.

Furthermore, a majority of the results from the learning impact studies that included an examination of some traits of students' motivation (e.g., self-efficacy) and attitude towards learning in the E-Model environment, found that students' motivations and attitudes were not negatively impacted by their learning experiences in the E-Model environment. Only one study mentioned that some students experienced mixed feelings regarding their learning experiences in the E-Model environment (Webel, Krupa, &McManus, 2017). This result was not surprising given that 27% of the 163 respondents who provided comments in the current study were negative. Some respondents liked certain aspects of the E-Model (i.e., going at your own pace) but expressed frustrations with other aspects outlined in Table 26.

Developing and validating a survey instrument that could be used to assess the impact that the E-Model environment had on students' psychological well-being was a first step toward understanding how it impacted mathematics learning. Construct validity results revealed the potential generalizability of the EMMS to assess whether the E-Model learning environment was supportive of students BPNS. The results were supported by the *G-H* Latent and Observed indices for assessing replicability and the fact that data were collected from two difference institutions of higher learning. Exploration of the initial 44 items of the EMMS produced 32 items with four parsimonious and reliable factor solutions.

Notably, the results of the current research study were promising. There were no major differences between the perceptions of students learning in a more student-centered learning environment, relative to the EMMS factors, at neither of the institutions that participated in the study. While there was a statistically significant difference between the institutions. Further analyses revealed that the driving force of that statistical significance was due to older respondents (at least 39 years old) who were predominately students at the community college.

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APPENDIXES

Appendix A

To Whom It May Concern,

I am a Doctoral student working toward a PhD in Evaluation, Statistics, and Measurement in the Educational Psychology and Research program at The University of Tennessee. I am currently an Associate Professor of Mathematics at Pellissippi State Community College. According to the National Center for Academic Transformation (NCAT), your institution participated in a project called Changing the Equation from 2009 to 2012. The website indicated that your institution successfully implemented the Emporium model for course redesign of your developmental math courses.

I have developed an instrument that can potentially be used to learn more about students' psychological needs as it relates to learning in an Emporium model environment. In order to proceed with the validation process of the instrument, I would need to survey students who have taken a course designed using the Emporium model. I would like to know, is the Emporium model currently being used for developmental math courses at your institution? If so, how can I proceed to gain support to have my survey administered to a select group of students?

I would greatly appreciate your response.

Regards,

Terry O Gibson Jr.
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Jennifer Ann Morrow, PhD
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jamorrow@utk.edu

Appendix B

Participant's Recruitment Letter

STUDENT,

You have been selected to participate in an anonymous survey regarding your experiences in your developmental mathematics course at Stark State College. I am a doctoral student at the University of Tennessee Knoxville working to complete a Ph.D. in Evaluation, Statistics, and Measurement.

There are four sections of the survey. Each section will ask you questions about your experiences learning mathematics in an environment in which you used a computer learning software, worked in a lab or computer classroom, and the importance of having an instructor/tutor to assist you.

INCENTIVE

By receiving this invitation to participate in the survey, you will automatically be entered into a random drawing even if you do not choose to participate in the survey. You will have the chance to win one of seven Amazon gift cards, electronically, ranging in value from $25 to $100.

$100 $50 $50 $25 $25 $25 $25

If you choose to participate, click on the link below to access the survey and read the consent form to proceed. You must be at least 18 years of age to participate in the survey and drawing. Your participation in this research is voluntary and would be greatly appreciated.

Follow this link to the Survey:

Or copy and paste the URL below into your internet browser:

Terry O Gibson Jr.
Doctoral Candidate
The University of Tennessee Knoxville
(865) 225-2313
tgibso10@vols.utk.edu

Doctoral Chair
Jennifer Ann Morrow, PhD
Associate Professor of Educational Psychology
University of Tennessee
Phone: (865-974-6117
jamorrow@utk.edu

Follow the link to opt out of future emails:

Appendix C

Participant's Informed Consent

AGE VERIFICATION
I am at least 18 years of age.
NO or YES

INTRODUCTION
You are invited to participate in a research study titled, *Development and Validation of the Emporium Model Motivation Scale* conducted by Terry O Gibson Jr., a Ph.D. student at the University of Tennessee. The purpose of the study is to gather information about students' motivations of learning mathematics in a non-traditional course setting.

PARTICIPANTS' INVOLVEMENT
Your participation in this study involves answering questions about your motivations of learning mathematics using a computer software, your experiences in a lab or computer classroom and importance of the instructor/tutor and overall learning experience in an environment called the Emporium Model (E-Model) learning environment. This survey should take you approximately 15 minutes or less to complete. Participation in this study is completely voluntary.

RISKS
All research carries some risk, however there are minimal risks to you. If you become uncomfortable sharing your experiences, then you are free to skip any question or stop the survey at any time. If you decide to finish the survey, know that all data obtained will be protected to maintain your confidentiality.

BENEFITS
The information that you provide is valuable and can be used to enhance the learning experiences of students in non-traditional learning environments, especially for learning support mathematics courses designed to help improve students' mathematical skills. Furthermore, this information will be used to guide future research efforts for improving the quality of learning in more student-centered learning environments.

CONFIDENTIALITY
The information you enter through the survey will be anonymous because your responses will not be linked to any identifiers. Only the researchers will have access to your answers and the data will be stored in a secure location. No references will be made in any reports that could link you as a participant to the study or the data. You may withdraw from the study at any time without penalty and without loss of benefits to which you are otherwise entitled. If you do not wish to participate in this research, then simply close the web browser window.

CONTACT INFORMATION
If you have questions at any time about the study or the procedures, or you experience adverse effects as a result of participating in this study, you may contact the lead researcher at the University of Tennessee, Terry O Gibson Jr. (865-225-2313; tgibso10@vols.utk.edu), Doctoral

Chair, Jennifer Ann Morrow at (865-974-6117; jamorrow@utk.edu). If you have questions about your rights as a participant, contact the University of Tennessee IRB Compliance Officer, at (865-974-7697; utkirb@utk.edu).

INCENTIVE

You will be given the opportunity to participate in a drawing for one of seven Amazon gift cards electronically. The rewards are one $100, two $50, and four $25 gift cards. You may enter the drawing whether you choose to participate in the survey or not. If you prefer not to participate, select "NO" on the next page and you will be directed to enter your drawing information. If you choose to participate, select "YES" on the next page and you will be prompted to complete the survey and enter your drawing information. I would greatly appreciate your participation.

CONSENT

I have read and understood the above information and would like to indicate my consent.

Do you consent to participating in the survey?

NO or YES

Appendix D

THE EMPORIUM MODEL MOTIVATION SCALE (EMMS)

Please read each statement carefully and select the response that most closely represents your level of agreement with learning in an Emporium Model (E-Model) environment. *Note: An* ***E-Model*** *learning environment is one in which you utilized a* ***Computer Learning System (CLS)****, which is software used for learning mathematics where you received assistance in a lab or computer classroom from an* ***instructor/tutor*** *for the semester.*	1=Strongly disagree 2=Disagree 3=Slight disagree 4= Neither agree nor disagree 5=Slightly agree 6=Agree 7=Strongly agree
1. Learning mathematics at a pace that was suitable for me gave me a sense of choice in the E-Model environment.	
2. The E-Model environment helped me increase my confidence in my abilities to do mathematics.	
3. I had a satisfying experience learning mathematics in the E-Model environment.	
4. I often did not feel very competent learning mathematics in the E-Model environment. R	
5. I felt a greater sense of control over how I was learning mathematics in the E-Model environment.	
6. The E-Model environment helped me improve my mathematical communication skills (***communicating in written and verbal forms***).	
7. I had a pleasant experience learning mathematics in the E-Model environment.	
8. I was able to increase my knowledge of mathematical skills in the E-Model environment.	
9. I felt a greater sense of responsibility for my own learning in the E-Model environment.	
10. The E-Model environment helped me gained life-long learning skills.	
11. Learning mathematics in the E-Model environment was an interesting experience.	
12. I felt a sense of accomplishment while learning mathematics in the E-Model environment.	
13. I felt a greater sense of ownership of what I was learning in the E-Model environment.	
14. The E-Model environment helped me gain a greater appreciation for mathematics.	
15. Learning mathematics in the E-Model environment was an enjoyable experience.	
16. I often did not feel capable of learning mathematics in the E-Model environment. R	
17. I felt like I had a choice learning mathematics in a way that supported my learning abilities in the E-Model environment.	
18. The E-Model environment prepared me for college level course work.	
19. Learning mathematics in an E-Model environment aroused my curiosity.	

Please read each statement carefully and select the response that most closely represents how true the statement reflects your connection with the instructor/tutor as it relates to receiving assistance in a Lab or computer classroom. *Note: The **instructor/tutor** refers to an individual who was trained to assist you when you needed help when visiting the Lab or computer classroom.*	1= Not at all true 2= Untrue 3= Slightly untrue 4= Neither true nor untrue 5= Slightly true 6= True 7= Exactly true
20. I liked the instructor/tutor that I came in contact within the E-Model environment.	
21. I got along with the instructor/tutor I came in contact within the E-Model environment.	
22. I kept to myself and didn't have a lot of contact with the instructor/tutor in the E-Model environment. R	
23. I considered the instructor/tutor I regularly worked with in the E-Model environment to be my friend.	
24. The instructor/tutor in the E-Model environment cared about me.	
25. There were not many instructors/tutors in the E-Model environment that I connected with. R	
26. The instructor/tutor in the E-Model environment that I worked with did not seem to like me much. R	
27. The instructors/tutors in the E-Model environment were friendly towards me.	
Please read each statement carefully and select the response that most closely represents how true the statement reflects your beliefs about using a Computer Learning System (CLS). *Note: A **Computer Learning System (CLS)** is the **software** that contained your math curriculum that you used either in a lab or computer classroom or away from campus.*	1= Not at all true 2= Untrue 3= Slightly untrue 4= Neither true nor untrue 5= Slightly true 6= True 7= Exactly true
28. I believe that using a Computer Learning System (**CLS**) could be of value for me.	
29. I believe that a CLS is useful for improved concentration.	
30. I think that using a CLS is important for my improvement in learning mathematics.	
31. I think using a CLS is a worthwhile technology.	
32. I think that using a CLS would improve my study habits.	
33. I am willing to use a CLS again because I think it is useful for learning mathematics.	
34. I believe that using a CLS could be beneficial for learning mathematics.	
35. I believe using a CLS could help me do better in my college level mathematics course.	
36. I would be willing to use a CLS again because it has value for me.	

Please read each statement carefully and select the response that most closely represents how true the statement reflects your strategies for learning.	1= Not at all true 2= Untrue 3= Slightly untrue 4= Neither true nor untrue 5= Slightly true 6= True 7= Exactly true
37. When studying in the E-Model environment, I tried to think through a topic to decide what I was supposed to learn from it rather than just reading it over.	
38. When I became confused about a math problem I was working on, I always tried to figure it out on my own.	
39. Before studying new concepts, I often skimmed the material to see how it was organized.	
40. When studying in the E-Model environment, I asked myself questions to make sure I understood the concepts.	
41. I tried to change the way I approached learning mathematics concepts in order to fit the course requirements.	
42. When studying in the E-Model environment, I tried to determine which concepts I didn't understand well.	
43. I tried to change my approach to learning the concepts when they were difficult to understand.	
44. When studying in the E-Model environment, I tried to set goals for myself in order to direct my activities.	

R = Reverse Code

Open-ended Question

Please provide any additional information that would help us further understand your learning experiences in the E-Model learning environment.

Demographics

The following demographic information will be used to describe the participants of the research study and used in specific analyses to learn more about attitudes and motivations with respect to different groups of students. If you do not wish to provide this information, then you can choose ***Prefer not to answer***.

1. What is your gender?

Female Male Prefer not to answer

2. What is your ethnicity/racial background?

American Indian or Alaska Native
Asian
Black or African American
Hispanic or Latino

Native Hawaiian or Other Pacific Islander
White
Other (please specify): ________________________
Prefer not to answer

3. What is your age range?
18-24, 25-31, 32-38, 39-45, 46-52, 53-59, 60 or over Prefer not to answer

4. How many semesters did you attempt or, did it take you to, complete your Learning Support Mathematics course or modules?

1 Semester 2 Semesters 3 or more semesters I don't know Prefer not to answer

Additional comments:

Appendix E

Academic Motivation Subscale : Identified Regulation

Please read each statement carefully and select the response that most closely represents the degree of correspondence to the following question. ***Why do you go to college?***	1=Corresponds not at all 2=Corresponds a little 3=Corresponds more than a little 4=Corresponds somewhat 5=Corresponds more 6=Corresponds a lot more 7=Corresponds exactly
1. Because I think college will help me better prepare for the career I have chosen.	
2. Because college will enable me to enter the job market in a field that I like.	
3. Because college will help me make more informed choices about my career options.	
4. Because I believe that college will improve my skills in my chosen career.	

Appendix F

Successful Projects

According to the NCAT website, the following institutions fully carried out the redesign plans and had successfully implemented the E-Model during the *Changing the Equation* (CTE) program initiative from 2009 – 2012:

- Bowling Green Technical College
- Cochise College
- Cossatot Community College of the University of Arkansas
- Guilford Technical Community College
- Heartland Community College
- Laramie County Community College
- Leeward Community College
- Lurleen B. Wallace Community College
- Manchester Community College
- Mountwest Community & Technical College
- Nashville State Community College
- Northern Virginia Community College
- Northwest-Shoals Community College
- Oakton Community College
- Pearl River Community College
- Robeson Community College
- Somerset Community College
- Stark State College
- Volunteer State Community College
- West Virginia University at Parkersburg

VITA

Terry O Gibson, Jr. began his post-secondary education after graduating from high school in 1996. He earned a Bachelor's of Science degree in Mathematics with a minor in Education from Savannah State University (SSU) in 2001. Following his undergraduate education, he received a graduate assistantship to attend Tennessee Technological University (TTU) in Cookeville, TN where he earned a Master's of Arts degree in Curriculum and Instruction in 2003. Additionally, he received a teaching assistantship from Middle Tennessee State University (MTSU) in Murfreesboro, TN where he began teaching College Algebra. He earned another Master's degree in the Science of Teaching Mathematics, in 2005.

In January 2006, Terry worked as an Instructor of Mathematics at MTSU teaching introductory college-level mathematics courses. He mainly taught College Algebra, Finite Mathematics, Mathematics for General Studies, and Applied Calculus. He worked as an instructor for the next three and a half years until he received a tenure track position at Pellissippi State Community College in Knoxville, TN to start the Fall 2009 academic year.

Terry is currently a tenured Associate Professor of Mathematics. During the first seven years, he work in the Transitional Studies Department (TSD). Within the department, he worked in the Learning Support Mathematics Program facilitating student-centered learning environments. He also worked on the hiring committee and as the supervisor of the Learning Commons during that time.

In 2015, TSD was phased out, as a result of a State mandate, at which time he transferred to the Mathematics Department where he taught College Algebra, Introductory Statistics, and co-requisite college-level gateway courses. Working in TSD inspired him to pursue a Ph.D. In 2014, Terry was accepted in Evaluation, Statistics, and Measurement (ESM) program in the

Educational Psychology and Counseling Department at the University of Tennessee, Knoxville (UTK). During his graduate education, he worked on both individual and team evaluation projects. Terry graduated from UTK in August 2019.