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

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Essential to college success is effective transitions management. Supporting healthy psychological well-being is integral to transitions, particularly for academic remediation efforts. Unfortunately, to date, no known self-report instrument exists that can be used to assess students' psychological well-being in more student-focused self-directed learning settings, such as the Emporium Model (E-Model) design for course instruction. The objective of the current study was to begin the development and validation of the Emporium Model Motivation Scale (EMMS), designed to assess the effectiveness of student-focused learning settings by adopting items from various instruments rooted in Self-Determination Theory (SDT). Data were collected from a random sample n = 463 respondents from a U.S. community college and 4-year public university. Exploratory Factor Analysis (EFA) using oblique methods produced four parsimonious and reliable factors (ω > .85). Using standardized factor score estimates, findings revealed that compared to 4-year college and younger students, community college students and older respondents were more autonomous and receptive to the E-Model design for course instruction and valued the interpersonal interactions with the instructors and tutors.

Keywords: Survey Development, Exploratory Factor Analysis, Transitions, Self-Determination Theory Motivation

As students transition to college, they are faced with various challenges that can impact successful transitions, persistence, and motivation to pursue academic aspirations (Grabau, 2011; Karmelita, 2020). A significant barrier to student success is student enrollment in learning support courses (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). Estimates have shown upwards of 60% of students at community colleges need learning support (Piercey & Aly, 2019). This creates hurdles for higher education institutions seeking to make transitions to college a smooth and rewarding experience. Transition challenges can be mitigated when institutional initiatives include mathematics learning support, given the significance of the "relationship between the cognitive and affective factors" to impact students' confidence in their abilities to succeed in learning support courses or programs

(Bonham & Boylan, 2011, p. 4). A growing trend addressing these challenges has been redesigning learning support mathematics courses to be more student-focused by adopting the Emporium Model (E-Model) design for course instruction (Twigg, 2011).

Since the initial development of the National Center for Academic Transformation (NCAT) in 1999, redesign efforts of *learning support mathematics* (LSM) courses or programs (i.e., developmental mathematics) and high enrollment in introductory college-level courses (e.g., College Algebra or English) have grown in popularity to combat the growing concerns of low success and retention rates of students enrolled in these courses (Ashby, Sadera, & McNary, 2011; Bonham & Boylan, 2011; Piercey & Aly, 2019). NCAT was a non-profit organization that provided course redesign resources to create cost-effective actively-engaged learning spaces where a *computer learning system* (CLS – e.g., ALEKS, Hawk's Learning System, Pearson's My Math Lab, or Lumen Learning Online Homework Manager) was a centralized component of the learning process. The success of NCAT initiatives brought on a wave of course redesign enthusiasts interested in fostering more student-centered learning that became increasingly popular following the implementation of the program initiative, *Changing the Equation,* from 2009 to 2012 (Twigg, 2013). Changing the Equation focused on redesigning LSM courses or programs at community colleges by implementing the E-Model design for course instruction – one of six course redesign models that required replacing lecture-based instruction with student-centered actively-engaged learning experiences through NCAT (Twigg, 2011).

Research suggests that programs using the E-Model design for course instruction are better suited for the more autonomous or self-directed learners than the less autonomous learners (Williams, 2016). However, research suggests that the E-Model can provide opportunities for the less autonomous learners to become more autonomously natured through autonomy-supportive instructional behaviors (Bray & Tangney, 2017). Self-directed learners are goal-oriented, good managers of their time, and use learning strategies to help them succeed (Cho & Heron, 2015). In addition, they are learners who tend to exhibit high levels of self-regulation of activities and work toward internalizing the value and usefulness of activities to render the desired outcome (Cho & Heron, 2013). The potential problematic issue for learners in the E-Model learning space is the absence of needed autonomy-support of their *basic psychological needs* (BPN). These needs are elements of Self-Determination Theory (SDT), which asserts that all individuals have a natural intrinsic desire to strive for *autonomy*, *competence*, and *relatedness* within unique social settings (Ryan & Deci, 2017). When external barriers impede the BPN, one's ability to thrive and grow within these settings is hindered. For students learning in more self-directed or student-focused experiences, receiving the needed autonomy support allows them to become more autonomous, develop confidence in their abilities, and feel a sense of belonging to the social experience. To this end, great insights can be obtained by examining the psychological well-being of students, given the significance of correlations found between psychological traits, student performance, and mathematics achievement (Cho & Heron, 2015; Kargar, Tarmizi, & Bayat, 2010; Skaalvik, Federizi, & Klassen, 2015). When E-Model environments are autonomy-supportive of students' BPN, the experience maximizes students' potential to strive and grow on their journey toward acclimating to the college experience and achieving their goals and aspirations.

The E-Model

Essential components. The success of the E-Model depends on the implementation of 10 essential elements displayed in Table 1. These fundamental elements consist of the Core Structural Elements, which form the foundational aspects of the E-Model across instructional designs, and the Strategic Operational Elements, which are based on interactions within the learning space implemented uniquely across instructional designs. However, the components support active-student engagement to maximize discourse between support staff and students. Additionally, some E-Models are 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 and any other concerns students have. For the most part, course delivery is in a computer learning lab where students use a CLS to complete their individualized mathematics curriculum (Twigg, 2011). Notably, merely developing a computer lab or computer classroom and incorporating a CLS does not constitute an E-Model course redesign; an E-Model redesign depends on intertwining all essential elements (Twigg, 2011). Additional information can be found at https://www.thencat.org/Guides/Math/TOC.html.

Table 1 *The 10 Essential Elements of the E-Model Design*

Core Structural Elements	Strategic Operational Elements
• Redesign whole course learning environments.	• Ensure active student engagement.
• Modularize the course content.	• Provide ongoing assessment with computerized feedback.
• Require mastery learning.	• Provide one-on-one access to trained professionals.
• Measure learning outcomes, completion rates, and cost-efficiency.	• Ensure the availability of adequate time on tasks.
• Computerize all learning environments using a CLS.	• Monitor student success and provide needed assistance.

Theoretical Framework

The assessment of students' learning experiences in the E-Model environment encompasses four needs. These are 1) autonomous learning needs, 2) educational technology appreciation, 3) instructor-relatedness, and 4) utilizing metacognitive self-regulated learning strategies (MC-SRLS). These motivational traits form the theoretical framework to assess the effectiveness of the E-Model methodology in being autonomy-supportive of students' BPN.

Autonomous learning needs. Several underlining theories provide a framework for the development of the EMMS. The current study's overarching theoretical framework is Self-Determination Theory (SDT; Ryan & Deci, 2017). SDT asserts that all individuals have an innate desire to strive for a sense of autonomy (i.e., the need to feel free and self-directed), competence (i.e., the need to feelcapable of performing), and relatedness (i.e., the need to feel a sense of connection or belonging), which are elements that encompass the BPN to excel and become more fully-functioning within unique social settings. Ryan and Deci (2017) identified a continuum of motivation that ranges from amotivation (i.e., lacking the motivation to act) to intrinsic motivation (i.e., one who experiences enjoyment of an action). Within these extremes are four types of extrinsic motivation (i.e., the continuum of relative autonomy). Of these, external and introjected regulations have an external locus of control. They are lower quality autonomous motivations, while identified and integrated regulations have an internal locus of control and are higher quality autonomous motivations (Ryan & Deci, 2017). These higher-quality autonomous regulators are contributing factors to the EMMS.

In theory, self-determined students should thrive in autonomy-supportive learning spaces (Reeve & Cheon, 2021). Throughout a course or program, students whose learning was impacted 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 due to these influential external factors. On the other hand, when the environment is not autonomy-supportive, it can cause "need frustration" and negatively influence students' motivation, which could cause them to digress toward relying on external means to progress through the course or program or hinder students' ability to thrive in the learning space or worse, become amotivated (Bray & Tangney, 2017; Ryan & Deci, 2017). This viewpoint centers around the effectiveness of the E-Model design to be autonomy-supportive of students' BPN and contribute to successful college transitional experiences that include both academic and student support services to minimize barriers to student success and retention (Karmelita, 2020).

Educational technology appreciation. Central to the E-Model learning experience is educational technology or the CLS (Twigg, 2011). These interactive software technologies are designed to supplement or deliver the instructional curriculum. When implemented effectively, educational technologies, particularly in mathematical educational settings, can add value to the learning experience in the form of "efficiency tools" by supporting the "speed and accuracy of computations" while enhancing students' mathematics learning (Bray & Tangney, 2017, p. 257). Despite this claim, evidence suggests its effectiveness falls short (Oates, 2011; Selwyn, 2011; Wright, 2010). Other researchers have found that, for some students, computer-assisted learning can harm students learning potential, particularly for students who have preconceived negative perceptions about their abilities to perform, which can ultimately affect their motivation to succeed (Kargar et al., 2010). Nevertheless, the selection, design, and delivery of subject matter content using educational technologies should enhance but not hinder students' learning experiences. Students' perceived use or value of educational technologies can provide insight into the effectiveness of these technologies in supporting students' learning experiences in the E-Model.

Instructor-relatedness. Relatedness is fundamental to interpersonal interactions within social contexts, such as educational settings that encompass one's need for "contact, support, and community" (Ryan & Powelson, 1991, p. 6). Within more self-directed learning spaces, instructor-relatedness plays an essential role in providing needed support to overcome psychological barriers and achieve success academically and beyond. Elements of autonomy-supportive instructional behaviors (e.g., listening to students, encouraging students' efforts, and supporting their abilities) in contrast to controlling forms of instructional behaviors (e.g., making demands or using controlling language such as have to) were found to be positively correlated with student learning outcomes (Jang, Reeve, & Deci, 2010; Reeve & Jang, 2006) as well as impacted student engagement (Reeve, 2012). More specifically, needed autonomy support can be delivered in two forms (i.e., emotional 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), while instrumental support is related to forms of instruction (e.g., explaining a mathematical concept, modeling a problem, providing guidance or inquiry; Federici & Skaalvik, 2014) or assistance with the CLS given its central significance to the E-Model design. Therefore, success within more self-directed learning spaces depends on students' connection to the instructor or support personnel in autonomy-supportive learning settings to allow students to build mathematical confidence and motivation to learn (Bray & Tangney, 2017; Williams, 2016).

Metacognitive self-regulated learning strategies. According to Gagne, Ryan, and Bargmann (2003), educational settings that supported students' BPN mediated the relationship between autonomy-supportive environments and positive outcomes. Incorporating metacognitive self-regulated learning strategies (MC-SRLS) into the implementation process increases autonomy. Metacognition is a process of monitoring one's cognition (Rhodes, 2019). When combined with SRLS, the process represents gaining ownership of one's learning through regulation. According to Pintrich, Smith, Garcia, and McKeachie (1991), MC-SRLS consists of three processes: planning, monitoring, and regulating. Each process specifies an activity that students engage in as part of the learning process. In general, planning involves choosing appropriate strategies (e.g., setting goals or selecting a specific strategy for the task) and allotting resources (e.g., managing time on tasks or seeking help from support personnel) that influence learning outcomes (Schraw, 1998). Monitoring involves specific tasks that help students assess their understanding of the material. For example, engaging in self-inquiry or self-quizzing of course content is a form of monitoring. Finally, regulating involves evaluating the effectiveness of one's ability to take control over their learning and reflecting on whether the chosen strategies are practical (Schraw, 1998). In other words, regulating is an ongoing process of "appraising the products and efficiency of one's learning" (Schraw, 1998, p. 115).

Purpose of the Study

The current study aims to complete a construct validity assessment of a newly developed instrument designed to measure students' perceptions of the effectiveness of the E-Model approach in supporting students' BPN. To date, no known publicly available validated survey instrument exists. Therefore, development and validation procedures seek to identify latent factors and examine interactions between derived latent constructs and demographic variables to underscore the impact of learning in more student-focused settings designed for the more autonomous or self-directed learners.

Research Questions

1. Do items of the EMMS produce parsimonious factor solutions (*RQ1*)?
2. Do derived factors of the EMMS satisfy internal consistency reliability with $\omega \geq .70$ (*RQ2*)?
3. Do type of college and age predict the EMMS factors (*RQ3*)?

Method

Participants

Respondents were from a Midwestern community college (COLLA; $n = 241$) and a Southeastern 4-year public university (COLLB; $n = 222$). The combined population of students from both institutions enrolled in a learning support mathematics course or introductory college-level mathematics course utilizing the E-Model design for course instruction was $N = 15{,}000$. We used the CheckMarket (n.d.) online sample size calculator for survey research to determine the sample for this population. The recommended sample size for a population of 15,000 at a 95% confidence level and 0.05 margin of error is 375. Therefore, the survey instrument was distributed to a random sampling frame of the target population at each institution (i.e., COLLA; $n = 3{,}211$ and COLLB; $n = 2{,}752$) for a total ($n = 5{,}963$). A combined response rate of approximately 8.4% ($n = 500$) was received. Of this random sample, 37 incomplete cases were removed from the dataset since more than 20% of their survey responses were missing. The remaining sample ($n = 463$) was used to prepare the data for analysis. Table 2 is a display of the demographic information. A majority of participants were in the age range 18 – 24 (67%), White (63%), female (75%), and those who completed their course work in one semester (64%). Additionally, there were an approximately equal number of Black (12%), and Hispanic (13%) respondents, approximately 5% were Asian, and another 4% of respondents identified as Other (e.g., biracial [Black/White, White/Asian, Black/Indian, and Arab/mixed raced]).

Measures

The four essential components that support self-directed learning are autonomous learning needs (AUTOLE), educational technology appreciation (EDTECH), instructor-relatedness (RELATE), and learning strategies (LEARNS). These constructs measured students' perceptions of learning effectiveness within the E-Model environment. The following discusses the origin of the EMMS items and includes psychometrics, sample items, and the response scale used to measure constructs.

The learning support mathematics program perception instrument (LSMPPI). The 37-item instrument was used as part of an evaluation project of an LSM program with three subscales: The Technology Assessment Scale with 10 items and two factors, the Learning Environment Assessment Scale with 15 items and three factors, and the Motivation Assessment Scale with 12 items and three factors. The instrument produced eight parsimonious factors, all with adequate internal consistency reliability of at least 0.73. More

Table 2 *Demographic Information*

Demographics	(n)	(%)
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		
Non-White	158	34.1
White	290	62.6
College		
COLLA	241	52.1
COLLB	222	47.9
Semester		
1 Semester	296	63.9
2+ Semesters	139	30.0

Note. n=Sample size, %=Percentage, *COLLA*=Community College, *COLLB*=University, $n = 463$.

specifically, the 7-item factor measuring higher quality autonomous motivation (e.g., "The E-Model environment helped me gain a greater appreciation for mathematics.") had satisfactory internal consistency reliability (ω = 0.92) for Motivation Assessment Scale, in which all 12 items were adopted for the current study. The subscale's detailed psychometric properties can be found in Gibson, Morrow, and Rocconi (2020). The items were measured on a 7-point Likert type scale ranging from 1=Strongly disagree to 4=Neither agree nor disagree to 7=Strongly agree.

The intrinsic motivation inventory (IMI; CSDT, 2022). The IMI is a 45-item instrument with seven subscales designed to assess respondents' motivation to engage in an activity: 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 0.79 (McAuley, Duncan, & Tammen, 1989). All nine of the value/usefulness items were adopted and edited to be domain-specific in the current study to assess the extent to which respondents value educational technology (e.g., "*I think that using a CLS would improve my study habits.*"). In a recent study, the 9-item factor measured higher quality autonomous motivation (i.e., identified, integrated, or intrinsic) than lower quality (i.e., external or introjected). In addition, it produced satisfactory internal consistency reliability, α = 0.92 (Schutte et al., 2017). The items were measured on a 7-point Likert type scale ranging from *1=Not at all true* to *4=Somewhat true* to *7=Extremely true*.

The basic psychological need satisfaction scale (BPNS; CSDT, 2022). The 21-item scale had been shown to have adequate internal structure and internal consistency reliability for each of the three subscales (Deci et al., 2001). Deci et al. (2001) reported satisfactory reliability values of the constructs: autonomy (7-items; α = 0.79), competence (6-items; α = 0.73), and relatedness (8-items; α = 0.74). The internal structure and consistency of the factors were supported in a recent study with similar Cronbach's alpha coefficients (α > 0.70; Sevari, 2017). Only four of the six competence items could be adopted for a more student-centered type learning environment (e.g., "*I often did not feel very competent learning mathematics in the E-Model environment.")*. In the current study, the items were measured on a 7-point Likert type scale ranging from *1=Strongly disagree* to 4=*Neither agree nor disagree* to *7=Strongly agree*. On the other hand, all eight relatedness items were adopted and edited to be domain-specific (e.g., "*I liked the instructor/tutor I came in contact with, in the E-Model environment."*). These items were measured on a 7-point Likert type scale ranging from *1=Not at all true to 4=Somewhat true to 7=Very true*.

The motivated strategies for learning questionnaire (MSLQ; Pintrich et al., 1991). The 81-item instrument is designed to measure college students' motivation (five factors) and the use of different "self-regulated learning strategies" (nine factors). The motivation subscale factors consist of 31 items with Cronbach's alpha coefficients ranging from 0.62 to 0.93. The different self-regulated learning strategies factors comprised 50 items with Cronbach's alpha coefficients ranging from 0.52 to 0.80. The MC-SRLS subscale consists of twelve items. Eight were adopted and revised to be domain-specific (e.g., "*When studying in the E-Model environment, I tried to determine which concepts I didn't understand well."*). The MC-SRLS was found to have adequate reliability in a recent study, α = 0.79 of high school students in Singapore (Chow & Chapman, 2017). The items were measured on a 7-point Likert type scale ranging from *1=Not at all true* to *4=Somewhat true* to *7=Very true*.

The adoption of newly developed items. The development of new items pertained specifically to outcomes experienced by students learning in the E-Model environment. The development of these items is discussed in the following section. After a review of the initial 20 items, eight were adopted for the current study (e.g., "*I felt a greater sense of control over how I was learning mathematics in the E-Model environment."* or "*I had a satisfying experience learning mathematics in the E-Model environment."*). The items were designed to measure higher quality autonomous motivation than lower quality, as defined by Ryan and Deci (2017). The items were measured on a 7-point Likert type scale ranging from *1=Strongly disagree* to *4=Somewhat agree* to *7=Strongly agree*.

Academic Motivation Scale (AMS; Vallerand, **Pelletier, & Blais,** ***1992).*** The 28-item 7-factor scale was based on the principles of Self-Determination Theory (SDT; Ryan & Deci, 2017). The AMS measured intrinsic motivation (to know, accomplish things, and experience stimulation), extrinsic motivation (external, introjected, and identified regulation), and amotivation. The internal structure was established using Confirmatory Factor Analysis with adequate mean alpha reliability = 0.81 and mean test-retest correlation = 0.79. Identified regulation was one of the four levels of motivation on the continuum of extrinsic motivation that measured low to high-quality autonomous motivation (Ryan & Deci, 2017). The identified regulation subscale of the AMS was used to assess convergent validity to reduce the effects of survey fatigue. The items maintained originality and were used to assess academic motivation. 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 type scale ranging from *1=Corresponds not at all* to *4=Corresponds moderately* to *7=Corresponds exactly*.

Procedure

Item development. 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: a review of research on redesigning LSM courses and programs. The second stage focused on developing and adopting 20 potential new items using survey research and design techniques (Colton & Covert, 2007), including adopting and revising 36 items from the four instruments previously discussed. Finally, the third stage assessed face and content validity through instrument testing and expert review.

Following the literature review, a professor of social psychology with research experience and knowledge of motivation theory assessed the content validity of the 20 newly developed items. Procedures 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 and combined with the 36 items adopted from other instruments for 44 initial items of the EMMS. Additionally, a review of all 44 items was performed by a sample of 18 students enrolled in an LSM course to assess item face and content validity. These students shared similar characteristics as the participants of the target population. Students received the items electronically and were asked to provide feedback regarding the readability, terminology used, and clarity of sentence structure. Upon review, items were revised to reflect the feedback received.

Recruitment and data collection. Recruitment of respondents began with an initial letter to representatives of participating postsecondary institutions. These institutions were identified through NCAT resources and had participated in a course or program redesign initiative using the E-Model methodology. Following IRB approval, the data collection process began. A request to collect data was sent to each institution for a representative random sample of the target population. An anonymous link to the survey was created within the Qualtrics survey software and distributed to the target population of participants. Notably, the random sample consisted of students who had enrolled in an E-Model course from fall 2016 through spring 2018, regardless of whether students completed or attempted completion of the course or program. The specified period was chosen to reduce the effects of history and maturation to increase the likelihood of more accurate responses from respondents. In addition, participants were entered into a raffle to win one of several Amazon gift cards.

Research Design. The current study is a nonexperimental research design. Correlational, survey and multivariate methods are used to analyze data and address the three overarching research questions. Before these analyses were performed, preliminary descriptive analyses and visual plots of variables were inspected for possible issues (e.g., missing data, outliers, normality, coding issues, and spelling errors). No more than 5% of data were missing, and outliers were recoded to be within $|\pm 3|$ standard deviations of the mean for analyses following EFA (see Tabachnick & Fidell, 2019). Analyses were carried out in two stages. The initial stage investigated the internal structure of the EMMS and the internal consistency reliability of derived factors. FACTOR was used to perform EFA (Ferrando & Lorenzo-Seva, 2017) to analyze the polychoric correlation matrix. Unweighted Least Squares (ULS) extraction and Promax rotation methods were recommended for ordinal data and correlated factors (Gaskin & Happell, 2014). Since no one method is flawless (Osborne, 2014), multiple methods were used to determine the number of factors to retain (i.e., Kaiser's eigenvalue > 1 criterion, Velicer's MAP, Horn's PA, and BIC dimensionality test). Ordinal omega coefficients with acceptable values ($\omega \geq 0.70$) were computed in R using the MBESS package to assess the internal consistency reliability (Dun, Baguley, & Brunsden, 2014).

Since factor score estimates are indeterminate (i.e., having infinite solutions; DiStefano, Zhu, & Mindrila, 2009), we computed several factor score estimate indices (i.e., the *factor determinacy index* [FDI] and *marginal reliabilities* [MR]; Ferrando & Lorenzo-Seva, 2018). An FDI index > 0.90 and MR > 0.80 were considered acceptable indices to ensure estimates were an accurate representation of participants' "true" score responses (Ferrando & Lorenzo-Seva, 2018). Additionally, *generalized H* (*G-H*) Latent and Observed indices were computed to assess the generalizability and replicability of the factor structure, which assesses how well a factor is defined by its common items with an established acceptable threshold > 0.80 for all factors (Ferrando & Lorenzo-Seva, 2018).

The second stage involved correlational and multiple regression analyses. Correlational analysis was performed to assess convergent validity between the EMMS factors and the identified regulation subscale of the AMS to provide evidence of higher-order autonomous motivation. Convergent validity was to be evidenced with statistically significant inter-correlations defined by Cohen's effect size values for product-moment correlations (i.e., r = .10 [small], .30 [medium], and .50 [large]; Cohen, 1992). In contrast, multiple regression analyses regressed the EMMS factors onto college and age predictor variables.[1] Diagnostic analyses assessed the adequacy of our multiple regression models (i.e., normality, linearity, outliers, multicollinearity, homoscedasticity, and independence of residuals; Ott & Longnecker, 2016). Additionally, with at most 3.3% of cases or variables with missing data, multiple imputations in FACTOR were used.

Results

Latent constructs and reliability of EMMS factors

A review of the Legacy Dialog plots suggested a slight violation of multivariate normality with reasonable linearity. Mardia's asymmetric test showed a significant kurtosis $p < .0001$, whereas skewness was not, $p = 1$ at a 0.05 level of significance. The test provided evidence to use Polychoric correlations, given ordinal data will most likely be asymmetric (Gaskin & Happell, 2014). 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, p. 78) supported factorability. A 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 for robust analysis. After several iterations, 12 variables were removed from the analysis, consisting of cross-loadings, violation of multicollinearity (> 0.90; Tabachnick & Fidell, 2019), and variable removal to improve communality to 0.54. The remaining 32 items formed a parsimonious four-factor solution of the EMMS. Notably, Table 3 displays the bivariate correlations between the EMMS factors and the identified regulation subscale of the AMS. Only instructor-relatedness produced a positive, statistically significant correlation with the identified regulation subscale of the AMS (r = 0.11, p = 0.014 with a small effect size based on Cohen's criterion for the product-moment correlation.

Table 3 *Bivariate Correlations Between EMMS Factors and Identified Regulation*

	AUTOLE	EDTECH	RELATE	LEARNS	AMS
AUTOLE	1				
EDTECH	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 Needs, **EDTECH**=Educational Technology Appreciation, **RELATE**= Instructor-Relatedness, **LEARNS**= Learning Strategies, **AMS**= Academic Motivation Scale, *$p < .05$, ** $p < .01$, $n = 463$.

RQ1 and RQ2. The retention of a four-factor solution was hypothesized *a priori,* given that many items were derived from other validated and reliable survey instruments. As discussed previously, several methods for retaining factors were reviewed. The modern methods: BIC, MAP, and PA, suggested the retention of three factors, whereas Kaiser's eigenvalue > 1 rule suggested the retention of four factors. Table 4 lists the eigenvalues and percentage of variance extracted per factor. Validity and reliability evidence and the *G-H* Latent and Observed indices produced acceptable values supporting a 4-factor solution. The *G-H* Latent

[1] Preliminary analyses were investigated to discern any meaningful differences between demographics provided in Table 2 regarding EMMS factors as dependent variables (DV). Correlations between DVs and semester ranged from r = -0.04 to 0.07, rendering the variable meaningless to consider in any future analysis (Tabachnick & Fidell, 2019). Only college and age produced significant differences following MANOVA. Similarly, multiple regression analysis on all other demographics produced the same outcome: college and age as predictors.

values ranged from 0.92 – 0.98, and the Observed values ranged from 0.85 – 0.98.

Table 4 *Extracted Eigenvalues and Explained % of Variance*

Factors	Eigenvalues[a]	Variance %	Cumulative Variance %
AUTOLE	19.94	62.31	62.31
EDTECH	2.49	7.79	70.10
RELATE	1.63	5.08	75.18
LEARNS	1.18	3.68	78.85

Note. [a]Polychoric correlations using ULS with Promax rotation in FACTOR.

***Autonomous learning needs* (*AUTOLE)*.** The first factor consisted of a 17-item subscale that accounted for approximately 62.3% of the variance with high reliability (ω = 0.98, 95% CI [0.97, 0.98]). These items assessed whether the learning environment was autonomy-supportive of students' learning needs. Factor score estimates ranged from 0.912 to 0.540 with respective sample items *("The E-Model environment helped me increase my confidence in my abilities to do mathematics."* and *"I had a satisfying experience learning mathematics in an E-Model environment."*)

Instructor-relatedness (RELATE). The second factor consisted of a 4-item subscale that accounted for approximately 7.9% of the variance and high omega (ω = 0.91, 95% CI [0.90, 0.92]). These items assessed the extent to which respondents agreed with the relatability of the instructor/tutor in the learning environment. Factor score estimates ranged from 0.957 to 0.784 with respective sample items *("I liked the instructor/tutor I came in contact with, in the E-Model environment."* and *"The instructor/tutor in the E-Model environment cared about me."*).

Educational technology appreciation (EDTECH). The third factor, composed of a 6-item subscale, accounted for approximately 5.1% of the variance with a highly reliable omega (ω = 0.96, 95% CI [0.96, 0.97]). These items assessed the extent to which respondents valued using a CLS. Factor score estimates ranged from 0.866 to 0.724 with respective sample items *("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."*).

Learning Strategies (LEARNS). The final factor consisted of a 5-item subscale accounting for the least amount of variance (3.7%) with an adequate omega (ω = 0.89, 95% CI [0.88, 0.91]). Items assessed the extent to which respondents used LEARNS during their learning experiences. Factor score estimates ranged from 0.903 to 0.629 with respective sample items *("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."*).

Accuracy and reliability of factor score estimates. The factor score estimates computed in FACTOR were deemed accurate and reliable. The FDIs for all factors were > 0.90 and ranged from 0.99 – 0.95. Reliability of the factors to be a true estimate of the population score produced MR values > 0.80; values ranged from 0.98 – 0.92.

RQ3. Demographic variables were recoded to specify a reference variable and indicator variable – such that, the public university and the youngest age group (18 – 24) were the reference variables. The first multiple regression analysis determined the effects on AUTOLE by type of college and age. The overall multiple regression analysis indicated that autonomous learning needs were impacted by college and age, $F(6, 456) = 4.07$, $p < 0.0005$, $R^2 = 0.05$, and Adj. $R^2 = 0.04$. Both college and age accounted for 4% of the variation in AUTOLE. Respondents from the community college had a statistically significant positive impact ($\beta = 0.13$, $sr_i^2 = 0.11$). Regarding age, respondents from ages 46 – 52 had significantly higher AUTOLE scores than those in the reference group (18 – 24), $\beta = 0.12$, $sr_i^2 = 0.11$.

The second multiple regression analysis determined the effects on EDTECH by type of college and age. The overall multiple regression analysis indicated that EDTECH was also impacted by college and age, $F(6, 456) = 4.45$, $p < 0.0002$, $R^2 = 0.06$, and Adj. $R^2 = 0.04$. Both college and age accounted for 4% of the variation in EDTECH. Respondents from the community college significantly positively impacted EDTECH ($\beta = 0.11$, $sr_i^2 = 0.09$). Consistent with the previous result regarding age, respondents ages 46 – 52 significantly impacted EDTECH ($\beta = 0.13$, $sr_i^2 = 0.12$) when compared with the reference group (18 – 24).

The third multiple regression analysis determined the effects on RELATE by these variables. The overall multiple regression analysis showed that RELATE was also impacted by college and age, $F(6, 456) = 9.8$, $p < 0.0000$, $R^2 = 0.11$, and Adj. $R^2 = 0.10$. Both college and age accounted for 10% of the variation in RELATE. The unique contribution by college was positive and statistically significant ($\beta = 0.29$, $sr_i^2 = 0.23$). In other words, the interpersonal connections between students and the instructors or tutors were positively impacted by respondents from the community college. Regarding age, respondents from the same age group 46 – 52 scored higher on RELATE than the 18 – 24 group ($\beta = 0.13$, $sr_i^2 = 0.12$).

The final multiple regression analysis determined the effects on LEARNS by college and age. The overall multiple regression analysis showed that LEARNS was impacted by college and age. $F(6, 456) = 4.22$, $p < 0.0004$, $R^2 = 0.05$ and Adj. $R^2 = 0.04$. Both college and age accounted for 4% of the variation in LEARNS. Community college respondents scored higher on metacognitive self-regulated learning strategies ($\beta = 0.19$, $sr_i^2 = 0.15$) than respondents from the four-year public university. In contrast, respondents 53 + scored higher than those 18 – 24 on the same construct ($\beta = 0.10$, $sr_i^2 = 0.10$).

Discussion

The study's purpose was to develop and begin the validation process of a survey instrument designed to assess the extent of the E-Model to be autonomy-supportive of students' BPN. Investigations included the internal structure and reliability of the initial 44 items of the EMMS. In addition, interactions were examined between the EMMS and specific demographic variables (college and age). Furthermore, RQ1 examined the uniqueness of the items of the EMMS to produce parsimonious constructs. EFA analysis produced four parsimonious latent subscales: autonomous learning needs (17 items), instructor-relatedness (4 items), educational technology appreciation (5 items), and metacognitive self-regulated learning strategies (6 items). RQ2 assessed internal consistency reliability and produced highly reliable omega coefficients where all $\omega \geq 0.89$. Additionally, the accuracy and reliability of factor score estimates exceeded the recommended minimum, with factor determinacy indices ranging from 0.98 – 0.99 and marginal reliabilities ranging from 0.92 – 0.98 for each factor. Finally, an assessment of the potential for generalizability produced satisfactory G-H indices (i.e., a measure of how well factors were defined by respective common items), which exceeded the minimum (i.e., > 0.80) with indices of at least 0.85 for both the *G-H* Observed and Latent variables (Ferrando & Lorenzo-Seva, 2018).

Pearson's r bivariate correlations between the EMMS factors and the identified regulation subscale of the AMS (Table 3) showed only a positive, statistically significant correlation between instructor-relatedness and identified regulation subscale ($r = 0.11$), which is a small effect (Cohen, 1992). Results were not the desired outcome; however, they are debatable. The factors of the EMMS had medium to high positive statistically significant inter-bivariate correlations. Theoretically, the domain-specific items of the EDTECH subscale were 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, 2017; Schutte et al., 2017).

Furthermore, the items of the identified subscale of the AMS were not altered to be domain-specific (i.e., specific to students assessing enrollment in the E-Model course rather than why they go to college), which could have weakened the relationship between the EMMS factors and the identified regulation subscale – thereby, highlighting discriminate validity between the EMMS factors and the identified regulation subscale of the AMS. However, any meaningful interpretation between instructor-relatedness within the E-Model and the reasons students go to college could have suggested that the "conscious valuing" respondents placed on the reasons why they go to college expressed higher levels of autonomy (concerning identified regulation) than the "conscious valuing" respondents placed on their learning experiences in the E-Model environment. Clearly, the identified regulation subscale of the AMS was not the best measure to assess convergent validity.

RQ3 examined how the EMMS measures were uniquely explained by the type of college and the age of participants. When controlling for age, findings suggest phenomena at the community college impacted all EMMS measures. Most notable, students at the community college valued the importance of interpersonal interactions with the instructor/tutor more than students at the public university. A reason for this outcome could be due to class size. Typically, community college class sizes are smaller and allow these interpersonal relationships to develop more where students are more likely to receive personalized attention (Chen, 2019). Another reason could be implementing the strategic operational elements at the respective institutions discussed previously.

Similarly, when controlling for college, findings suggest that older respondents (i.e., those aged 46+) reported greater autonomous learning needs, more educational technology appreciation, expressed higher importance of the interpersonal connections with the instructor and reported utilizing more metacognitive self-regulated learning strategies compared with traditional-aged students 18 – 24. Research offers a possible reason for these findings. Naturally, students between 18 – 24 will be less autonomous at the beginning of their college experiences. Research suggests that students become more autonomous during their first four years of college (Wachs & Cooper, 2002). Other research indicates that students will become more autonomous when they separate from reliance on their parents and assume more adult-related responsibilities (Cullaty, 2011). Although statistically significant, effect sizes were small (i.e., f^2 ranging from 0.05 to 0.12; Cohen, 1992).

Limitations

While no research is without its limitations, there are several limitations, in particular, worth mentioning. First, data were collected from a self-report survey, which has disadvantages. Participants' mood, environment, and ability to recall pertinent information could have biased responses. Furthermore, responses were not assessed for social desirability. Evidence suggests computer-mediated effects lessen social desirability susceptibility for self-report administration (Dillman et al., 2009). Second, while it is assumed that all participants were enrolled in courses that fully implemented the E-Model design, little is known about the inner workings of the ten essential components at the respective institutions. Third, while the low response rate presents cause for concern, the sample size is sufficient to model the regression relationships in the data. Existing research suggests representation from low response rates can accurately represent the data and be comparable to the representativeness of higher response rates, thereby minimizing bias concerns (Fosnacht, Sarraf, Howe, & Peck, 2017; Lambert, & Miller, 2014). Fourth, the FDI and MR indices produced acceptable values supporting the potential generalizability of the factors to be accurate and reliable. However, the lack of gender and ethnic diversity could affect the generalizability of the results. Despite limitations, the study provides convincing evidence of the construct validity and reliability of the EMMS items.

Implications

Integral to college success is transitions management (Musamali, 2019). An essential component of transitions management is healthy psychological well-being (Grabau, 2011). Results of the current study have both practical and theoretical significance regarding the extent to which student-focused learning experiences can be supportive of students' BPN (Ryan & Deci, 2017). Theoretically speaking, when social settings support the BPN, individuals thrive and are more willing to persist and more likely to be motivated internally to better manage disruptions from external factors (Ryan & Deci, 2017). Results suggest that the EMMS items can be used to assess the effectiveness of student-focused settings or environments implementing the E-Model design for course instruction. In addition, empirical evidence suggests that these learning settings are better suited for the autonomous learner but can provide opportunities for the less autonomous learner to become more autonomy-natured (Williams, 2016).

Practically speaking, several implications exist. First, the EMMS can evaluate whether social settings support autonomous learning needs related to affective factors and academic motivation (e.g., anxiety or self-efficacy; Bonham & Boylan, 2011). Second, the EMMS can assess the extent to which autonomy-supportive instructional behaviors influence instructor-relatedness to provide emotional or instrumental support (Federici & Skaalvik, 2014; Patrick et al., 2011). Third, the EMMS can assess the extent of the appreciation or value of using educational technology to enhance the learning experience. These technologies are a central component of student-focused actively-engaged learning experiences (Twigg, 2011). Anecdotal evidence suggests that adult learners transitioning to college have minimal technological skills, which can hinder student success (Karmelita, 2020). All the more reason to assess the impact of using educational technology to support students' BPN. Fourth, the EMMS can be used to assess the extent of the use of learning strategies to help students succeed. Using learning strategies is a sign that students develop into more self-directed learners (Cho & Heron, 2015). Finally, the EMMS can serve an essential role in evaluating the effectiveness of student-focused settings to support students' psychological well-being, mainly when transition experiences include mathematics learning support as an integral part of a student success initiative (Bonham & Boylan, 2011).

Future Research

The items of the EMMS can be adapted to be domain-specific. Therefore, future research should adapt items to assess the effectiveness of transitions programs to be autonomy-supportive of students' BPN. Empirical evidence suggests autonomous students who exhibit high self-efficacy are more motivated and more likely to handle disruptions during the transition to college (Grabau, 2011). Given that items of the EMMS were developed using a theoretical framework rooted in SDT, a necessary next step is to continue the validation process with a more representative sample using a confirmatory framework (e.g., Confirmatory Factor Analysis). Moreover, future research should re-evaluate convergent and examine divergent validity using more appropriate domain-specific subscales. Additional explorations should investigate the predictive nature of the EMMS items to provide insight into factors related to transitions, persistence, and academic motivation. Further explorations should include demographic variables and student outcome data (e.g., pre/post-test scores, GPA, etc.). The main objective is to use the EMMS items to assess the effectiveness of student-focused settings to be autonomy-supportive, contribute to successful college transition, and positively impact student success and retention.

Conclusion

Ensuring a smooth transition to college should be a top priority for post-secondary institutions. Students entering college are susceptible to a multitude of "dramatic" experiences that can profoundly affect academic motivation and psychological well-being (Grabau, 2011); their desire to be self-directed, competent, and feel connected to the college community (Ryan & Deci, 2017). Developing a survey instrument that could assess students' psychological well-being in more autonomous or student-focused settings was a first step toward exploring and validating the latent traits of the EMMS items. The EMMS is the only instrument developed to fulfill this purpose by targeting student-centered learning in post-secondary education.

Despite limitations, assessing the validity and reliability of the EMMS items produced four parsimonious factor solutions. Appropriate psychometric analysis suggests the potential generalizability of the EMMS to be supportive of students' BPN. However, results should be interpreted with caution given the low response rate and lack of gender and ethnic representation in the data. Results were further supported by *G-H* Latent and Observed indices for assessing replicability. While empirical evidence suggests that the E-Model methodology is better suited for the more self-directed learners (Williams, 2016), the implications of utilizing the EMMS can provide additional insight regarding the effectiveness of the E-Model in supporting the BPN of the less autonomous learners.

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