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A CRITICAL SUCCESS FACTORS MODEL FOR DIGITAL DISTANCE LEARNING

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Abstract:

Based on the prior two models of critical success factors (CSF) of online learning, this research presented a new CSF model that includes the use of mobile devices and tightly integrated constructs of self-regulated learning (SRL), intrinsic motivation, and extrinsic motivation. This new CSF model reflects the evolving nature of a CSF model in response to changing external environments, including the emergence of connectivism to support online education. Independent variables included in the study are the use of mobile devices, student motivation (intrinsic and extrinsic), student self-regulation, dialogue (instructor-student and student-student), instructor, and course design as potential determinants of online learning outcomes and student satisfaction. A total of 323 valid unduplicated responses from students who have completed at least one online course at a university in the Midwest were used to examine the structural model.

Keywords: Mobile Device Usage, Intrinsic Motivation, Extrinsic Motivation, Self-Regulated Learning, Perceived Learning Outcomes, Digital Distance Learning, E-Learning, Mobile Learning.

I. INTRODUCTION

The concept of e-learning, the use of computers in the learning context, is also related to various other concepts such as computer-assisted learning, computer-facilitated learning, learning management systems, computer-assisted education, and massive open online courses. Under each concept, researchers have researched the pedagogical models, instructional strategies, learning technologies, critical success factors (CSF) models of e-learning systems, etc.(Aparicio, Bacao, & Oliveira, 2016). This paper focuses on identifying CSF for digital distance learning systems.

This paper presents a new CSF model for digital distance learning based on recent survey data. The new CSF model is built on two previous models (Eom & Ashill, 2016; Eom, Ashill, & Wen, 2006), which have been successful and widely accepted in the online learning community. Eom, Wen, & Ashill's (2006) study of predictors of students' perceived learning outcomes and satisfaction has engendered numerous other online learning CSF studies. It has been identified as one of the top 10 most cited articles in empirical online learning between 2006-2021 (Ortega Azurduy, 2021) and one of the 100 most cited articles in all of business and management education research (J. B. Arbaugh & Hwang, 2015). Another follow-up article (Eom & Ashill, 2016) provided a historically-grounded conceptualization and incorporated more fully developed measures of course structure, learner, instructor, and participant interaction characteristics to revisit the question of key predictors of perceived learning outcomes and learner satisfaction. Especially the updated model improved its quality by adding self-regulated learning (SRL) as a CSF of online learning and deleting learning styles from the 2006 model (Sean B. Eom, Ashill, & Arbaugh, 2016).

This paper presents a new CSF model that includes the use of mobile devices as a CSF and tightly links three constructs of SRL, intrinsic motivation and extrinsic motivation. This paper aims to remedy further the second model's weaknesses (Eom & Ashill, 2016). They include learner motivation and self-regulation. Self-regulation had either mixed or no predictive effects on learning outcomes and satisfaction. Therefore, these learner characteristics (motivation and SRL) need to be re-examined. Reexamination of the theoretical framework and prior literature on SRL led us to build a new CSF model in which motivation and SRL are linked into an integrated construct. Besides, the use of the mobile device is included as a CSF so that the current improved model will better guide future researchers who develop and conduct online learning programs to improve students learning outcomes.

The major contributions of this study are that this is the first study that presents a CSF model for digital distance learning. As we will discuss later, online learning systems at most universities worldwide can be characterized as digital learning (see the section on digital distance learning systems for the definition. Nevertheless, most CSF studies today can be applicable only to desk-top based e-learning.

The following section provides the readers with a foundational concept of digital distance learning as a basis and justification of the new CSF digital learning model. Further, it explains why SRL and motivation constructs need to be linked. This is followed by the description of the research model, hypotheses development, and research methodology, including the development of a survey instrument to collect data, structural equation modeling (SEM) methodology, and the results of a partial least squares (PLS) analysis. We then discuss the study findings, implications for future university distance learning, and the directions for future research.

II. FOUNDATIONAL CONCEPTS

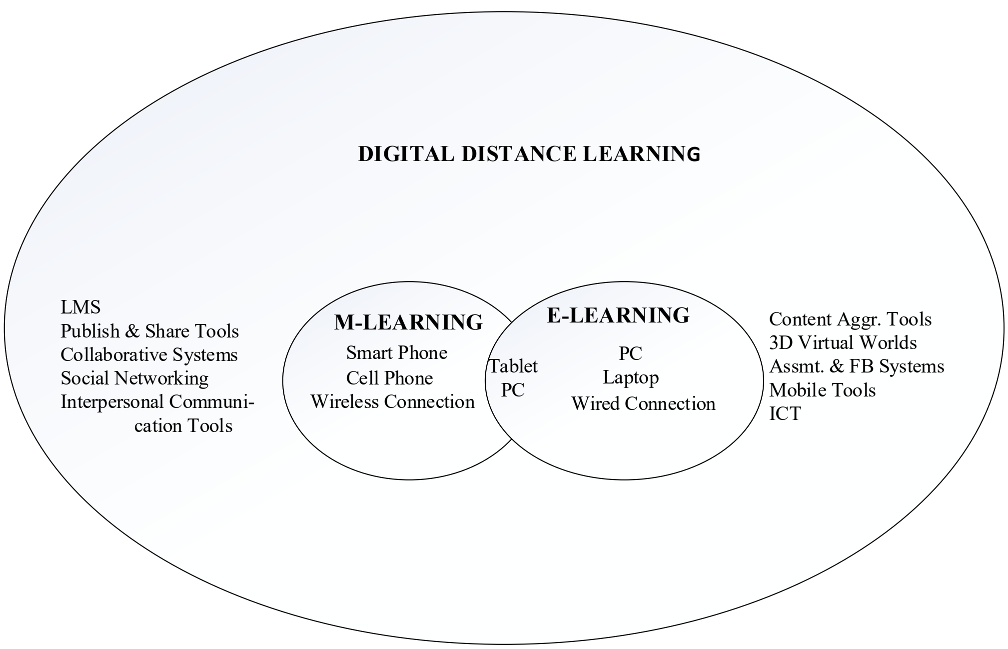
Digital Distance Learning Systems

According to the Pew Research fact sheet, as of January 30, 2022, 100 % and 96 % of U.S. adults owned cell phones and smartphones, respectively (https://www.pewresearch.org/internet/fact-sheet/mobile/). According to the Online College Students survey conducted in 2021 by Wiley Education Services (Capranos, Dyers, & Magda, 2021), online students were asked questions about the extent of the use of mobile devices when doing various online course-related activities. An online student sample of more than 3000 students is using a mobile device to do a wide range of course-related activities, including the following: Checking grades, assignment due dates, and course schedules (64%), Communicating with professors (47%), Communicating with fellow students (39%), etc. Other activities include using it as a portal into online learning management systems (LMS). Similar survey reports are also available (Clinefelter, Aslanian, & Magda, 2019; Magda, Capranos, & Aslanian, 2020).

WiFi-connected mobile devices have perpetually changed the landscape of distance learning. With the changing environment, digital distance learning (DDL) is a new phenomenon that has transformed the nature of distance learning to be a more powerful, effective delivery medium. It is a powerful and inclusive concept covering traditional face-to-face, e-learning, mobile, and ubiquitous learning. Due to online students' ever-increasing trend of using mobile devices in the online learning process, it is vitally important to include the use of mobile devices as a CSF of online learning.

Over the past decades, we have conducted many empirical research studies in each area that constitutes DDL. However, research on e-learning success has not paid proper attention to them. For example, the most influential articles on e-learning CSFs (Sean B. Eom, Ashill, & Wen, 2006; Sun, Tsai, Finger, Chen, & Yeh, 2008) failed to include the use of mobile devices as a CSF. Further, a recent scoping review of critical predictive factors of satisfaction and perceived learning outcomes in e-learning environments (Yunusa & Umar, 2021) also identified a taxonomy of predictive factors of satisfaction and learning outcomes with the exclusion of the use of mobile devices in support of e-learning processes.

According to Basak et al.(2018), digital learning is “a term that is increasingly replacing e-learning, and it concerns the use of information and communication technology (ICT) in open and distance learning.” The basic building blocks of digital learning are e-learning and m-learning. A consensus has not been reached yet in defining e-learning, m-learning, and digital learning (Grant, 2019; Moore, Dickson-Deane, & Galyen, 2011; Park, 2011; Peters, 2007). Figure 1 depicts digital distance learning systems that consist of e-learning and m-learning. The digital distance learning system is a digital technologies-based, purposeful and synergistic system of human entities (students and instructor) and nonhuman entities (LMS and information and communication systems) to optimize distance learning outcomes and student satisfaction. There is a dynamic relationship among student motivation, course design quality, instructor roles, and students’ academic engagement. There are many different ways of distinguishing e-learning, m-learning, and digital learning (Basak et al., 2018; S. Eom & Laouar, 2020; Keegan, 2005; Korucu & Alkan, 2011; Mottiwalla, 2007). Nevertheless, an undisputable element is using mobile devices to support learning processes. The figure is based on a hardware-driven classification of learning system taxonomy. Therefore, it is crucial to understand the roles of mobile devices in the digital distance learning processes and outcomes.



Notes: LMS = Learning Management Systems
Content Aggr. Tools = Content Aggregation Tools
Assmt. and FB Systems = Assessment and Feedback Systems
ICT = Information and Communication Technology

Figure 1: Digital distance learning systems (Source: [Eom 2022, p.15]

Linking SRL and Motivation

Pintrich (2004) provided a conceptual framework for assessing motivation and self-regulated learning in college students. According to the framework, self-regulation of learners' activities include the following: regulation of cognition, regulation of motivation and affect, regulation of behavior, and regulation of context. Therefore, self-regulated learning activities include the regulation of motivation.

Our previous two CSF models reviewed B.J. Zimmerman's contribution to a social cognitive view of self-regulated academic learning (Barry J. Zimmerman, 1989), an overview of the relationship between SRL and academic achievement (Barry J. Zimmerman, 1990), key subprocesses of SRL (B.J. Zimmerman, 1986). His fundamental contributions are the characteristics of self-regulated learners who are "metacognitively, motivationally, and behaviorally" active participants in their learning process and Self-regulated learners who use SRL strategies were positively associated with superior learning outcomes (Barry J. Zimmerman, 1990).

The critical difference between this study and our previous studies is the tight coupling of motivation and SRL activities, as the research model (Figure 2) exhibits. This tight coupling is based on a conceptual framework of Pintrich (2004) and a series of empirical studies (Boekaerts, 1996; Bruso & Stefaniak, 2016; Çetin, 2015; Sean B. Eom, 2015; Lim & Yeo, 2021).

III. A CRITICAL SUCCESS FACTORS MODEL FOR DIGITAL DISTANCE LEARNING AND HYPOTHESIS DEVELOPMENT

Figure 2 is built on two previous models (Sean B. Eom & Ashill, 2016; Sean B. Eom et al., 2006), which have been successful and widely accepted in the online learning community. Another follow-up article (Sean B. Eom & Ashill, 2016) provided a historically-grounded conceptualization and incorporated more fully developed measures of course structure, learner, instructor, and participant interaction characteristics to revisit the question of key predictors of perceived learning outcomes and learner satisfaction. Especially the updated model improved its quality by adding SRL as a CSF of online learning and deleting learning styles from the model.

Building a new CSF model for digital distance learning should be based on underlying theories of learning, as discussed in (Eom & Ashill, 2016). Our 2016 CSF model was built on the constructivist learning model, which assumes that knowledge is constructed rather than instructed. The constructivist model has two different seemingly antinomic schools of thought: constructivism (knowledge created individually and independently) and collaborativism (knowledge constructed socially and collaboratively). The eight independent constructs can be clustered into two schools of thought. Individual and independent knowledge discovery is possible with SRL and the individual student's motivation, while instructor roles and activities, Student-Student Dialogue (SSD), Student-Instructor Dialogue (SID), and course design all together function to create knowledge socially and collaboratively (Pintrich & Groot, 1990; Smith, 2001). The new CSF model in Figure 2 has a new CSF, mobile devices, which can be better understood within the theory of connectivism (Goldie, 2016; R, J.M., & J., 2019; Siemens, 2005).

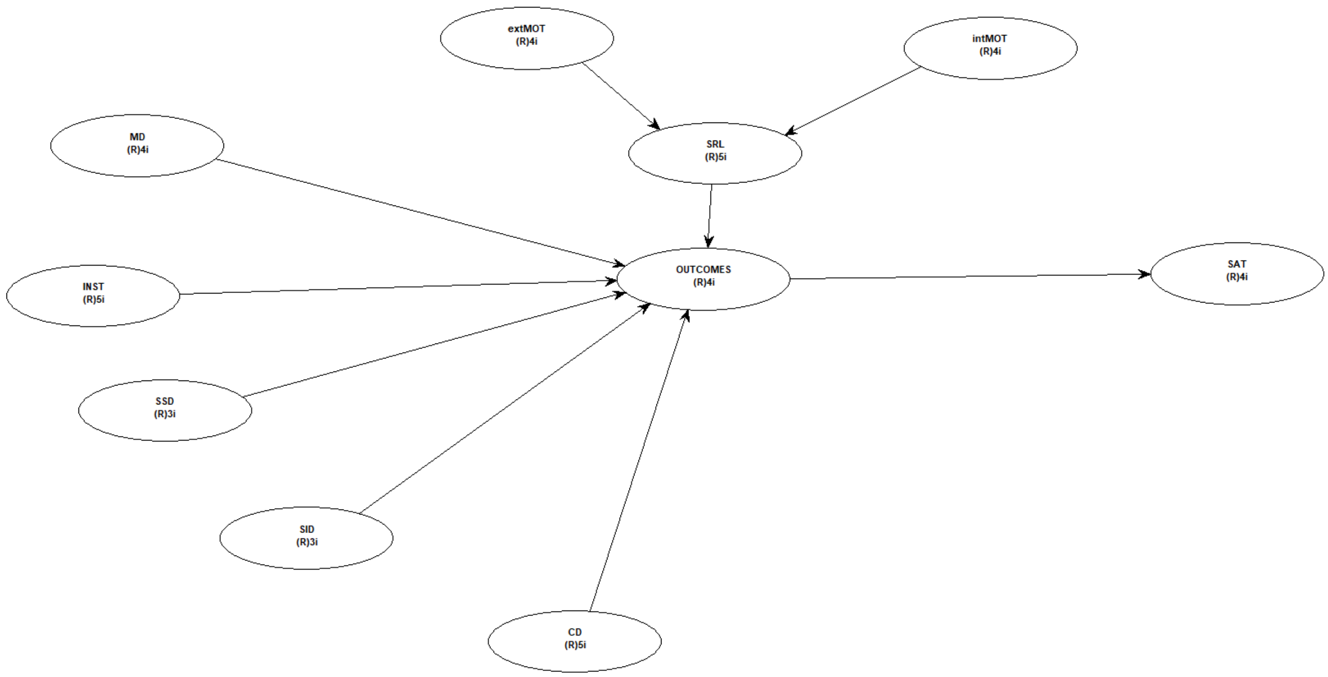


Figure 2: Research Model

Motivation and Self-Regulated Learning

Based on the discussion in section on linking SRL and motivation, We therefore hypothesize:

Hypothesis 1: Students’ intrinsic motivation in online courses is positively related to SRL.

Hypothesis 2: Students’ extrinsic motivation in online courses is positively related to SRL.

Hypothesis 3: Students’ SRL in online courses is positively related to perceived learning outcomes.

Mobile Device Use

The use of mobile devices positively affects student-instructor and student-student dialogues. It also facilitates self-regulation, positively affecting learning outcomes (Sean B. Eom, 2022; García-Martínez, Fernández-Batanero, Sanchiz, & Rosa, 2019; Sung, Chang, & Liu, 2016).

We therefore hypothesize:

Hypothesis 4: the use of mobile devices in online courses is positively related to students’ learning outcomes.

Instructor

Creating knowledge socially and collaboratively requires a set of coordinated activities such as SSD, SID, and course design. The roles of instructors in this process are to orchestrate them as discussion leaders, communicators, and course designers and to create a learning community (Arbaugh, 2010; Sean B. Eom & Ashill, 2016; Sean B. Eom et al., 2006; Hung & Chou, 2015; Pintrich & Groot, 1990; Smith, 2001; Wilson & Stacey, 2004).

We therefore hypothesize:

Hypothesis 5: Instructor activities in online courses are positively related to students' learning outcomes.

Instructor-Student Dialogue and Student-Student Dialogue

Interaction is a CSF that cuts the distance in e-learning and promotes positive online learning experiences (Boling, Hough, Krinsky, Saleem, & Stevens, 2012). Collaborativism assumes that knowledge is socially and collaboratively constructed through the shared understanding of a group of learners (Bruner, 1985; Vygotsky, 1978). Creating knowledge socially and collaboratively implies that students need interactions with fellow students and the instructor (Ayanbode, Fagbe, Owolabi, Oladipo, & Ewulo, 2022; Borokhovski, Bernard, Tamim, Schmid, & Sokolovskaya, 2015; Molinilloa, Aguilar-Illescas, Anaya-Sánchez, & Vallespín-Arán, 2018; Sher, 2009; Yu, Huang, Han, He, & Li, 2020).

In the e-learning literature, interaction and dialogue have often been used interchangeably. Many empirical studies have attempted to link the effects of all types of interaction (negative, neutral, and positive) to learning outcomes and satisfaction. But they failed to do so. In this study, dialogue refers to purposeful, constructive, meaningful interaction that each party values. Dialogue promotes learning through active participation and enables deep cognitive engagement for developing higher-order knowledge (Moore, 1997; Muirhead & Juwah, 2004). This study, therefore, focuses on the effects of meaningful interaction (dialogue) on perceived learning outcomes and satisfaction.

Therefore we hypothesize:

Hypothesis 6: Student-Instructor dialogue in online courses is positively related to students' perceived learning outcomes.

Hypothesis 7: Student-Student dialogue in online courses is positively related to students' perceived learning outcomes.

Course Design

Course design is concerned with the planning and design of the course structure. It is also concerned with the course's process, engagement, interaction, and evaluation. The Quality Matters (QM.) rubric is a widely accepted course design standard. QM. is an international organization representing broad inter-institutional collaboration and a shared understanding of online course quality (https://www.qualitymatters.org). The QM. rubric standards include four other categories: learner interaction, course technology, learner support, and accessibility and usability.

Empirical research strongly links course design and learning outcomes (Sean B. Eom & Ashill, 2016, 2018; My, Tien, My, & Quo, 2022; Tsang, So, Chong, Lam, & Chu, 2021).

Therefore, we theorize that course design and structure will strongly correlate with user satisfaction and perceived learning outcomes, primarily when course material is organized into logical and understandable components that are interesting and stimulate online learners' desire to learn. We thus hypothesize:

Hypothesis 8: Course design quality in online courses is positively related to students' perceived learning outcomes.

Learning Outcomes and Satisfaction

Online learning outcomes and satisfaction have been two major dependent constructs in empirical e-learning studies (Choe et al., 2019; Sean B. Eom & Arbaugh, 2011; Sean B. Eom & Ashill, 2016; Zhao, Bandyopadhyay, & Bandyopadhyay, 2020). In this study, learning outcomes are measured by the perceived level of students' quality of learning experience in online classes. Students' satisfaction is measured by their willingness to take online classes again or to recommend the instructor of online classes taken to other students. Thus, in line with existing research, we hypothesized:

Hypothesis 9: Perceived learning outcomes in online courses are positively related to students' perceived satisfaction.

IV. RESEARCH METHOD

A survey is used to collect data. WarpPLS 8.0 was used to test the research model (Kock, 2022). The following sections provide details of the survey instrument and sample.

Survey Instrument and Sample

Appendix A includes the survey questionnaire. The survey questions are listed according to different constructs with specific sources.

We collected 3,285 e-mail addresses from the student data files at the registrar's office with every online course delivered through the online program of a university in the Midwestern United States. The 34 survey questions were created using SurveyMonkey. The survey URL and instructions were sent to all valid e-mail addresses. We collected 323 valid, unduplicated responses from the survey.

Table 1. Student Characteristics

	Sample	Proportion (%)
Age		
< 20	78	24.15
21-30	130	40.25
31-40	48	14.86
41-50	45	13.93
51-60	20	6.19
>61	2	0.62
Total	323	100.00
Gender		
Male	111	34.37
Female	212	65.63
Total	323	100.00
Year in School		

Freshman	17	5.26
Sophomore	54	16.72
Junior	64	19.81
Senior	112	34.67
Graduate	76	23.53
Total	323	100.00

V. ANALYSIS AND RESULTS

Model Fit and Quality Index

Table 2 demonstrates that all 10 model fit and quality indices suggest a good model fit. The first three indices (average path coefficients (APC), average R-squared (ARS), and average adjusted R-squared (AARS)) are all significant at P<0001 level, which is much better than the recommended value at the 0.05 level (Kock, 2022). The model's predictive and explanatory power are well demonstrated, rated by the Average block variance inflation factor (AVIF) and average full collinearity variance inflation factor (AFVIF). AVIF is 2.633, which is less than the acceptable value <=5. Further, AFVIF is 2.633, which falls under the ideal threshold value. All other five remaining indices below illustrate high levels of predictive power.

Table 2. Model Fit and Quality Index

Model fit and quality indices

Average path coefficient (APC)=0.240, P<0.001
Average R-squared (ARS)=0.383, P<0.001
Average adjusted R-squared (AARS)=0.377, P<0.001
Average block VIF (AVIF)=2.281, acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)=2.633, acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)=0.527, small >= 0.1, medium >= 0.25, large >= 0.36
Simpson's paradox ratio (SPR)=1.000, acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)=1.000, acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)=1.000, acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)=1.000, acceptable if >= 0.7

Measurement (Outer) Model Estimation

Many researchers from various disciplines have used combined and cross-loadings to conclude that the measurement model has convergent validity. Two criteria are recommended as the basis for concluding that a measurement model has acceptable convergent validity: (1) the loadings should be 0.5 or higher, and (2) the P values associated with the loadings should be less than .05 (Kock, 2014; 2020a). Figure 2 shows the WarpPLS output of the combined loadings and cross-loadings. All reliability measures for both models were above the recommended level of .70 (Gefen, Straub, & Boudreau, 2000), thus indicating adequate internal consistency (Table 2). The average variance extracted scores (AVE) exceeded the minimum threshold of .5 (Fornell & Larcker, 1981), ranging from .51 to .87.

Table 3. Measurement Model Estimation

Constructs and Indicators	Loadings (>.7)	CRC (>.7)	AVE (>.5)
Intrinsic Motivation (intMOT)		0.828	0.547
intM1	0.753		
intM2	0.701		
intM3	0.772		
intM4	0.730		
Extrinsic Motivation (extMOT)		0.875	0.636
extM1	0.817		
extM2	0.745		
extM3	0.815		
extM4	0.812		
Mobile Devices (Mob)		0.924	0.753
mob1	0.879		
mob2	0.839		
mob3	0.881		
mob4	0.870		
Instructor		0.933	0.737
Inst1	0.892		
Inst2	0.844		
Inst3	0.786		
Inst4	0.877		
Inst5	0.890		
Student-Student Dialogue (SSdia)		0.947	0.855
SSdia1	0.918		
SSdia2	0.946		
SSdia3	0.911		
Student-Instructor Dialogue (SIdia)		0.962	0.895
SIdia1	0.952		
SIdia2	0.961		
SIdia3	0.925		
Course Design (CD)		0.927	0.719
CD1	0.841		
CD2	0.887		
CD3	0.849		
CD4	0.820		
CD5	0.843		
Self-Regulated Learning (SRL)		0.880	0.596
SRL1	0.784		
SRL2	0.805		
SRL3	0.803		
SRL4	0.650		
SRL5	0.808		
Learning Outcomes (Out)		0.916	0.732
Out1	0.809		
Out2	0.893		
Out3	0.846		
Out4	0.871		
Satisfaction (SAT)		0.929	0.769
Sat1	0.896		
Sat2	0.931		
Sat4	0.721		
Sat5	0.942		

Notes: Loadings are unrotated, and cross-loadings are oblique-rotated. S.E.s and P values are for loadings. P values < 0.05 are desirable for reflective indicators. Composite reliability coefficients (CRC), Average variances extracted (AVE)

Table 4. Correlations among latent variables

	intM	extM	MD	INST	SSD	SID	CD	SRL	OUT	SAT
intM	0.739									
extM	0.104	0.798								
MD	0.141	0.321	0.868							
INST	0.450	0.210	0.099	0.859						
SSD	0.371	0.223	0.158	0.589	0.925					
SID	0.426	0.204	0.114	0.842	0.613	0.946				
CD	0.463	0.278	0.135	0.801	0.537	0.730	0.848			
SRL	0.453	0.412	0.176	0.484	0.392	0.444	0.612	0.772		
OUT	0.269	0.207	0.141	0.556	0.425	0.540	0.528	0.404	0.855	
SAT	0.326	0.246	0.092	0.760	0.494	0.707	0.793	0.479	0.645	0.877

Notes: Square roots of average variances extracted (AVEs) are shown on diagonal. They should be higher than the correlational figures.

The composite reliability measure of internal consistency and average variance extracted (AVE) were used to assess construct reliability. Adequate internal consistency was demonstrated. All reliability measures met the 0.70 threshold (Gefen, Straub, and Boudreau, 2000). AVE scores ranged from 0.56 to 0.87 and were thus above the minimum threshold of 0.5 (Fornell & Larcker, 1981). Discriminant validity was also demonstrated (see Table 3).

Structural Model Results

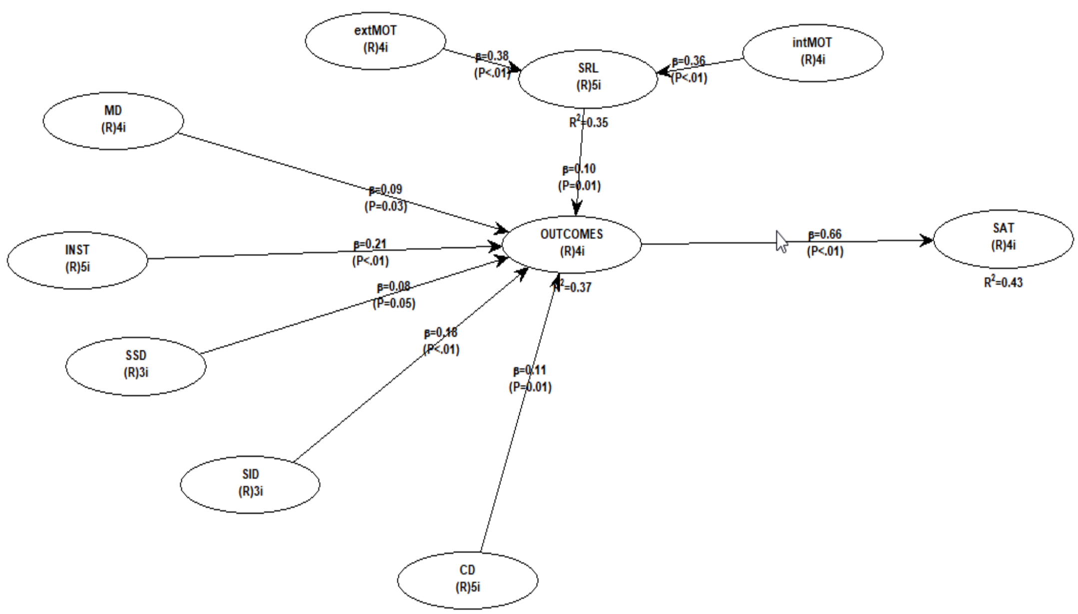


Figure 3: Structural Model Results

The structural model explained 37% of the variance in student learning outcomes and 43% of the variance in student satisfaction. Table 5 shows all hypotheses are supported. First of all, effects of motivations (intM and extM) on SRL are found to be statistically highly significant ($\beta = .359$, $p < .001$), and ($\beta = .377$, $p < .001$). When compared with the direct path modeling result (Sean B. Eom & Ashill, 2016), the integration of motivation into SRL produces meaningful results as intended. As shown in Table 6, disintegrated intrinsic and extrinsic motivation and SRL effects on learning outcomes produce less meaningful and illogical results. It is hard to interpret not significant roles of SRL on learning outcomes. Second, the effect of mobile device use on learning outcomes is positive and significant (β = .088, p = .033).

Table 5. Hypotheses Testing Results

Hypothesized Relationship	Stand. Coeff.	P-value		Results (Supported)
Effects on SRL (R^2 = .36)				
H1. intM -> SRL	0.359	< 0.001	****	Yes
H2. extM -> SRL	0.377	< 0.001	****	Yes
Effects on Learning Outcomes (R^2 = .37)				
H3. MD -> Out	0.088	0.033	**	Yes
H4. Inst -> Out	0.215	< 0 .001	****	Yes
H5. SSD -> Out	0.083	0.047	*	Yes
H6. SID -> Out	0.176	< 0.001	****	Yes
H7. CD -> Out	0.108	0.012	**	Yes
H8. SRL -> Out	0.105	0.014	**	Yes
Effects on Satisfaction (R^2 = .43)				
H9. Out-> SAT	0.657	<0.001	****	Yes

Notes Significance levels
****p < .001, ***p < .01, **p < .05, : *p < .10,   p>.10 not significant (ns).

Table 6. Hypothesis Testing Results with Direct links (IntM → Out, extM → Out, and SRL → Out)

Intrinsic Student Motivation (H1b)	+.10	2.68**	Yes
Extrinsic Student Motivation (H2b)	+.01	.08 n.s	No
Student Self-Regulation (H3b)	+.05	1.36 n.s	No

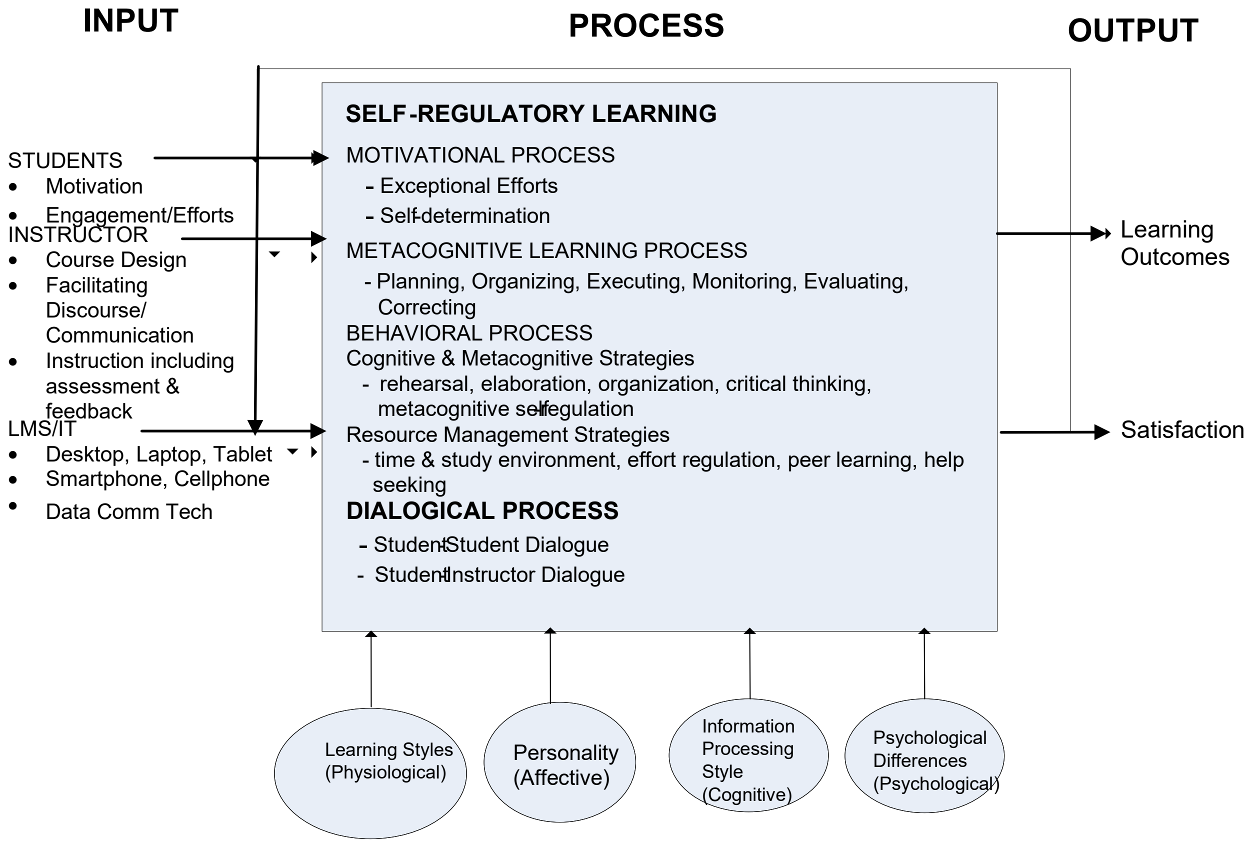


Figure 4: System's View of E-learning Success Model, Mobile Devices and Learning Outcomes
Adapted from Eom and Ashill (2016, p.148)

V.I CONCLUSION AND DISCUSSION

Built on the prior two models of CSF of online learning, this research presented a new CSF model that includes the use of mobile devices and tightly integrated constructs of SRL, intrinsic motivation, and extrinsic motivation. This new CSF model reflects the evolving nature of a CSF model in response to changing external environments, including the emergence of connectivism to support online education. This new CSF model allows us to manage several CSFs effectively to realize the potential for online learning. Today's online learning environment is significantly different from the e-learning environment characterized as desk-top computer-based and wired access to Internet-based education. Most students today use their mobile devices to access, and download course files, communicate, interact with fellow students and instructors, access the learning management systems, and complete their assignments.

Adding the use of mobile devices as a CSF has several implications. The affordances of mobile technology (MacCallum, Day, Skelton, & Verhaart, 2017) have strongly and positively impacted the learning processes and outcomes by overcoming the time and space constraints of traditional classroom learning. Therefore, mobile learning is characterized by anytime, anyplace, technology, mobility, and learners' mobility (El-Hussein & Cronje, 2010). Technology-mediated learning has progressed from e-learning to m-learning and digital learning (the union of desk-top-based e-learning and mobile device-based mobile learning). The learning process consists of SRL (Motivational, Meta-cognitive, and Behavioral) (Figure 4) and dialogical processes.

Consequently, the union of e-learning and m-learning has made distance learning a more effective delivery medium. It will significantly alter the learning landscape by converging several critical phenomena embedded in it: digital media, social media, user-generated media, BYOD (bring your own devices), open learning, and mobile learning. The power of mobile digital computing and communication devices enables distance learners to learn anywhere at any time. Consequently, various affordances of mobile intelligent devices are harnessed to positively enhance learning processes and outcomes.

The contributions of this paper to the knowledge in the digital learning area are as follows. This study is the first to include using mobile devices as a CSF of digital learning. The system's view of the holistic e-learning CSF model (Figure 4) incorporates the interdependent process. The use of mobile devices as an input to digital distance learning systems must positively affect the distance learning process to realize substantial learning outcomes and student satisfaction. The primary roles of mobile devices are to facilitate SRL and dialogical processes, as shown in Eom (2022).

Future research should explore to shed light on the relationship between the use of mobile devices and its moderating and mediating effects on each of the other CSFs, in addition to the relationship between the levels of intrinsic and extrinsic motivation, the learning process variables, and the cognitive learning outcomes (S. Eom, 2021; Sean B. Eom, 2022). Future research should include the expanding roles of digital distance learning to enrich life-wide learning, which is learning in different places (in their homes, at work, on the train, etc.) and lifelong learning throughout their lifetime.

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APPENDIX A: SURVEY QUESTIONS

1. What is your age?
2. What is your gender?
3. What is your year in school?
4. What is your area of study?

The Use of Mobile Devices (Self-developed based on (Clinefelter et al., 2019))

5. I frequently use mobile devices to ask questions and answer the questions posted on the learning management system such as Moodle by other students or the instructor in the online course I am taking (Md1).

6. I frequently use mobile devices to check my progress in the online course I am taking (Md2).

7. I frequently use mobile devices to communicate with other students and/or the instructor in the online course I am taking (Md3).

8. I frequently use mobile devices to access the course contents (PowerPoint files, assignment files, course announcements, etc.) in the online course I am taking (Md4).

Intrinsic Motivation (Pintrich et al., 1991)

9. In an online class like this, I prefer class material that really challenges me so I can learn new things (Int. M1).

10. In an online class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn (Int. M2)

11. The most satisfying thing for me in this online class is trying to understand the content as thoroughly as possible (Int M3).

12. When I have the opportunity in this online class to choose class assignments, I choose the assignments that I can learn from even if they don't guarantee a good grade (Int. M4).

Extrinsic Motivation (Pintrich et al., 1991)

13. Getting a good grade in this online class is the most satisfying thing for me right now (Ext. M1).

14. The most important thing for me right now is improving my overall grade point average, so my main concern in this online class is getting a good grade (Ext. M2).

15. If I can, I want to get better grades in this online class than most of the other students (Ext. M3).

16. I want to do well in this online class because it is important to show my ability to my family, parents, or others (Ext. M4).

Dialogue with Students (Sean B. Eom & Ashill, 2016)

17. I had positive and constructive interactions with other students frequently in this online class (SSDia1).

18. In this online class, the level of positive and constructive interactions between students was high (SSDia2).

19. In this online class, I learned more from my fellow students than in other classes at this university (SSDia3).

Dialogue with the Instructor (Sean B. Eom & Ashill, 2016)

20. I had positive and constructive interactions with the instructor frequently in this online class (SIDia1).

21. The level of positive and constructive interactions between the instructor and students was high in this online class (SIDia2).

22. The positive and constructive interactions between the instructor and students in this online class helped me improve the quality of the learning outcomes (SIDia3).

Self-Regulated Learning (Metacognitive) (Pintrich et al., 1991)

23. In the beginning, I set my goals and plan according to what I need to do to make desired learning outcomes (SRL1).

24. Even when study materials are dull and uninteresting, I keep working until I finish (SRL2).

25. I keep up with my grades in each course, and if one seems to be sliding, I will stress that class more in my studying (SRL3).

26. When I study for a test, I try to put together the information from class notes and from the book (SRL4)

Perceived Learning Outcomes (Sean B. Eom & Ashill, 2016)

27. The academic quality of this online class is on par with face-to-face classes I have taken (Out1).

28. I have learned as much from this online class as I might have from a face-to-ace version of the course (Out2).

29. I learn more in online classes than in face-to-face classes (Out3).

30. The quality of the learning experience in online classes is better than in face-to-face classes (Out4).

Perceived User Satisfaction (Sean B. Eom & Ashill, 2016)

31. I would recommend this instructor to other students (Sat1).

32. I would recommend this online class to other students (Sat2).

33. I would take an online class at this university again in the future (Sat3).

34. I was very satisfied with this online class (Sat4).

ABOUT THE AUTHOR

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