The Impact of the Use of Mobile Devices in University Distance Learning on Students’ Motivation and Perceived Learning Outcomes: An Empirical Investigation

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ABSTRACT
Mobile devices, primarily cell phones, smartphones, and tablet PCs, have gradually been introduced into the university campus and online education over the past several decades. The impact of the use of mobile devices on academic performance has been a subject of intense on-going investigations during this time. Prior empirical research studies focused on the impact of mobile devices on the learning process and learning outcomes. This research aims to answer whether the use of mobile devices in online courses influence intrinsic and extrinsic motivation to learn as well as perceived learning outcomes. A total of 323 valid and unduplicated responses from students who have completed at least one online course at a Midwestern university in the U.S. were used to examine the structural model, using SmartPLS v. 3.3.2. The results of this study show that the use of mobile devices positively affects students’ intrinsic and extrinsic motivation to learn. Furthermore, the intrinsic and extrinsic motivation positively affects the perceived learning outcomes. Integrating mobile technology enables educational institutions to design and build distance learning systems that allow students to be highly flexible with their locations and schedules in the learning process.

Author Keywords
Mobile device usage, intrinsic motivation, extrinsic motivation, distance learning, e-learning, mobile learning.

INTRODUCTION
Mobile devices, primarily cell phones, smartphones, and tablet PCs, have gradually been introduced into the university campus and online education over the past several decades. According to the Pew Research Center report (https://www.pewinternet.org/fact-sheet/mobile/), 99% of US adults aged 18-29 own a cell phone or a smart phone. This has changed the nature of the delivery mode in university education and led to the extensive use of mobile devices in the learning process. Campus Technology reported the results of a recent survey from Learning House and Aslanian Market Research on the extent of the use of mobile devices when doing various on-line, course related activities. These activities include accessing course readings, lecture files, learning management systems (LMS), communicating with professors and fellow students, finishing assignments, and conducting research assignments. The use of mobile devices for learning is common among university students, and the use of these devices provides nearly seamless continuity of formal learning for the increasingly mobile learner (Ally & Wark, 2018; H. J. So & Park, 2019; Xiao, Wang, Wang, & Pan, 2019).

The impact of the use of mobile devices on academic performance has been a subject of intense on-going investigations over the past several decades. Prior empirical research studies focused on the impact of mobile devices on the learning process, satisfaction, and learning outcomes (Arain, Hussain, Rizvi, & Vighio, 2018; S. B. Eom, 2017; Goh, Seet, & Chen, 2012; S. So, 2016; Zhonggen, Ying, Zhichun, & Wentao, 2019). They investigated the relationships between mobile device usage and four pivotal constructs (student-student dialogue, student-instructor dialogue, self-regulation, and learning outcomes) in university online education. It provided important empirical evidence in regard to the effects of mobile device usage on the perceived learning outcomes in university online education.

Their research was conducted to empirically test a research question posed by members of the Penn State World Campus Learning Design (LD) team. Mockus, et al (2011) explored how mobile devices could be utilized to provide instructional options (mobile learning, blended learning, etc.) for adult learners. Due to the absence of rigorous methodology and insufficient sample size, their study failed to produce meaningful and sweeping conclusions.

With sufficient sample size and rigorous methodology, our empirical research aims to answer the three research questions (RQs) described in the hypothesis development section.
The following sections present a theoretical foundation, the literature review, and the description of the research model and hypotheses development. We then discuss research methodology, including the development of a survey instrument, structural equation modeling (SEM) methodology, and the results of a partial least square (PLS) analysis of the research model. We then present the study findings and discussion, which includes the theoretical and practical implications for future university distance-learning.

A THEORETICAL FOUNDATION
Our research model is grounded in a system’s view of the e-learning success model. Based on a review of the past several decades of e-learning empirical research, a system’s view of the e-learning success model has emerged to advance our understanding of the effective management of critical success factors (CSFs) of e-learning (Fig. 1). This is an empirically tested, learning theory based, holistic model that demonstrates that learning outcomes and student satisfaction critically depends on three mediating constructs: student-student (SS) dialogue, student-instructor (SI) dialogue, and self-regulated learning (SRL) behaviors (S. B. Eom & Ashill, 2018). There are two characteristics that set this view apart from other e-learning empirical models: the significant reduction of the number of independent and dependent variables as well as the interdependence of the critical success factors with inputs, processes, and outputs.

Figure 1: System’s view of e-learning success model. (Source: Eom & Ashill 2016, p.189)

LITERATURE REVIEW
The influence of the use of mobile devices on academic performance has been a subject of intense on-going investigations, as briefly introduced in the introduction section. However, there is a dearth of empirical studies that test the relationship between the use of mobile devices/mobile applications and motivation. There are two broad lines of research exploring the relationship: what motivates people to use mobile devices and how mobile devices impact the students’ motivation to learn. Readers are referred to (Ann Jones & Issroff, 2007; A. Jones, Issroff, Scanlon, Clough, & McAndrew, 2006; Kim, Kim, & Kim, 2019) for the review the first area of this line of research.

How mobile devices impact the students’ motivation to learn
The second area of this line of research was to determine how mobile devices impact the students’ motivation to learn. Mockus, et al (2011) explored how mobile devices could be utilized to provide instructional options for adult learners. A goal of their research study was to determine how course content and information delivery on mobile devices impact the students’ motivation to learn. Their survey feedback showed that “content delivered on the mobile devices can motivate students to learn, but it needs to be engaging, meaningful, organized, and enjoyable.” According to the respondents, they want to be able to access all of the important course resources and be able to perform a wide variety of necessary learning tasks on their mobile devices. If learning activities are delivered on their mobile devices, they need to be tightly connected to the subject matter. Finally, the mobile content can be engaging, but it needs more interactive elements built-in so the
students are a part of an active learning process. The absence of rigorous methodology and insufficient sample size failed to produce the output of the research inquiry.

**RESEARCH MODEL AND HYPOTHESES DEVELOPMENT**

Our research was conducted to empirically test the research question posed by Mockus, et al (2011). The left side of research model, Figure 2, contains three exogenous/independent latent variables, while the right side includes one endogenous/dependent latent variable.

![Figure 2: Research model.](image)

**Mobile Technology and Motivation**

RQ1: Does the use of mobile devices in online courses influence intrinsic and extrinsic motivation to learn?

The use of mobile technology is a predictor that affects the learning process and learning outcomes. This is because of the functionalities of mobile devices. According to Ryan and Deci (2000, p. 56), intrinsic motivation is the psychological feature that makes an individual carry out an activity for its inherent satisfaction. This could be for fun or for the challenge entailed, rather than for some separable consequence. On the other hand, extrinsic motivation causes an individual to take an action toward a goal to attain a separable outcome, such as reward or recognition.

The survey results of Mockus, et al (2011) revealed that some students felt that having access to course material delivered on their mobile device enabled them to learn the material better than the same content presented in the traditional online format. It also revealed that the students felt that course material delivered on their mobile device improved their learning experience.

The survey’s “meaningful” criterion covered questions about the importance of student grades (extrinsic motivation) and the factors influencing their motivation to learn (intrinsic motivation). All respondents said that grades were very important to them. The survey asked the students if more content delivered on the mobile device would motivate them to learn. The respondents were evenly split with half of the students reporting that they would be more motivated to learn, and the other half reporting that their motivation would be about the same.

Therefore, we hypothesized:

H₁: A higher level of mobile technology use in online courses will be positively associated with a higher level of intrinsic motivation.

H₂: A higher level of mobile technology use in online courses will be positively associated with a higher level of extrinsic motivation.

**Motivation and Perceived Learning Outcomes**

RQ2: Do the intrinsic and extrinsic motivations to learn online influence perceived learning outcomes?
Student motivation is a psychological construct that activates the self-regulation process (Zimmerman, 2008). According to Castillo-Merino and Serradell-Lopez (2014), motivation has the most direct, positive, and significant effect on students’ achievements. Continuing research on motivation has produced some empirical evidence of the positive links between intrinsic motivation and satisfaction (S. B. Eom, Ashill, & Wen, 2006), motivation and student performance (Castillo-Merino & Serradell-Lopez, 2014), and individual players’ peer intrinsic and extrinsic motivation and intention to learn collaboratively and individually in a game-based learning environment (Kong, Kwok, & Fang, 2012). We therefore hypothesize:

H1: A higher level of intrinsic motivation in online courses will be positively associated with a higher level of perceived learning outcomes.

H2: A higher level of extrinsic motivation in online courses will be positively associated with a higher level of perceived learning outcomes.

**Mobile Technology and Learning Outcomes**

RQ3: Does the use of mobile devices in online courses influence perceived learning outcomes?

The survey results of Mockus, et al (2011) revealed that some students felt that having access to course material on their mobile device enabled them to learn the material better than the same content presented in the traditional online format. Furthermore, they felt that course material delivered on their mobile device improved their learning experience.

Therefore, we hypothesized:

H3: A higher level of mobile technology use in online courses will be positively associated with a higher level of perceived learning outcomes.

**SURVEY INSTRUMENT AND SAMPLE**

All model constructs were measured using five-point Likert scales with reflective indicators since they measured the same underlying phenomenon. With reflective measurement, all indicators are interchangeable, which is a key principle of reflective measures (Chin, 1998). We selected the survey questionnaire (Appendix A) from previous studies (S. B. Eom & Ashill, 2016, 2018; S. B. Eom et al., 2006). We collected the e-mail addresses of 3,285 students from the student data files archived with every online course delivered through the online program of a university in the Midwestern United States. The Institutional Review Boards (IRB) determined that the proposed research presents minimal risk and falls into Category 2 of research that is eligible for exemption from IRB approval. The survey questions were created using SurveyMonkey. The survey URL and instructions were sent to all of the e-mail addresses. A total of 323 valid, unduplicated responses were received from the students.

**METHODOLOGY**

The research model was tested using SmartPLS version 3.3.2 (Ringle, Wende, & Becker, 2015), which is the structural equation modeling (SEM)-based Partial Least Squares (PLS) methodology. This is a second generation, multivariate statistical method that can handle unobserved latent variables (constructs) and measurement errors. SmartPLS is a predictive research model in the initial exploratory stages of theory development. If the prior theory is strong and further testing is the objective of research, covariance-based SEM, such as LISREL, is a better choice. Furthermore, SmartPLS does not require specific data distributions. The evaluation of PLS-SEM is divided into two parts: measurement (outer) model and structural (inner) model.

**Measurement (Outer) Model Evaluation**

The measurement (outer) model defines the relationships of the latent variables (constructs) and their indicators. The evaluation of the reflective measurement model includes examining the following: (1) the indicator reliability values (squared outer loadings are 0.70 or higher; (2) the internal consistency reliability with several criteria such as Cronbach’s α, composite reliability; (3) the convergent validity with the average variance extracted (AVE); and (4) the discriminant validity (Hair, Hult, Ringle, & Sarstedt, 2017).

Table 1 shows the reflective measurement model validation results. All 17 indicator loadings are much higher than the recommended level of 0.70, thus indicating adequate internal consistency (Claes R. Fornell & Bookstein, 1982; Nunnally & Bernstein, 1994). The AVE scores were also above the minimum threshold of 0.5 (Chin, 1998; Claes R. Fornell & Larcker, 1981) and ranged from 0.677 to 0.906. When the AVE is greater than .50, the variance shared with a construct and its measures are greater than error. This level was achieved for all of the model constructs.

Construct validity is assessed through establishing both convergent and discriminant validities. Convergent validity refers to the extent to which a set of indicator variables load together and highly (loading >0.50) on their associated factors. Individual reflective measures are considered reliable if they correlate more than 0.7 with the construct they intend to measure. Table 1 shows that all of the loadings are higher than the threshold value 0.7. When indicator variables do not
cross-load on two or more constructs, each construct is said to be demonstrating discriminant validity. In PLS, discriminant validity was assessed using two methods. The first method examined the cross-loadings of the constructs and the measures. The second compared the square root of the average variance extracted (AVE) for each construct with the correlation between the construct and other constructs in the model (Chin, 1998; Claes R. Fornell & Larcker, 1981).

Table 1: Reflective outer model validation results.

<table>
<thead>
<tr>
<th>Construct Items</th>
<th>Indicators</th>
<th>Loadings (&gt;0.7)</th>
<th>Internal Consistency reliability (Composite Reliability&gt; 0.7 or higher)</th>
<th>Convergent Validity (AVE) (&gt; 0.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MD Use</td>
<td>Mob1</td>
<td>0.870</td>
<td>0.924</td>
<td>0.751</td>
</tr>
<tr>
<td></td>
<td>Mob2</td>
<td>0.862</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mob3</td>
<td>0.870</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mob4</td>
<td>0.864</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Int. Motivation</td>
<td>Int. M1</td>
<td>0.783</td>
<td>0.840</td>
<td>0.725</td>
</tr>
<tr>
<td></td>
<td>Int. M2</td>
<td>0.915</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ext. Motivation</td>
<td>Ext. M1</td>
<td>0.821</td>
<td>0.873</td>
<td>0.631</td>
</tr>
<tr>
<td></td>
<td>Ext. M2</td>
<td>0.808</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ext. M3</td>
<td>0.800</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ext. M4</td>
<td>0.777</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outcomes</td>
<td>Out1</td>
<td>0.872</td>
<td>0.912</td>
<td>0.723</td>
</tr>
<tr>
<td></td>
<td>Out2</td>
<td>0.908</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Out3</td>
<td>0.784</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Out4</td>
<td>0.833</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Discriminant validity is established when each observed variable loads highly on its theoretically assigned construct and not highly on the other constructs. Discriminant validity in PLS is assessed by comparing the square root of the AVE for each construct with the correlation between the construct and other constructs in the model. Adequate discriminant validity is manifested when the square root of the AVE for each construct is larger than the correlation between the construct and any other construct in the model (Claes R. Fornell & Larcker, 1981). Table 2 shows that the square root of each AVE (diagonal value) is larger than any correlation among any pair of latent variables, thus demonstrating discriminant validity.

Table 2: Assessing discriminant validity (the Fornell-Larker Criterion).

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Int. Motivation</td>
<td>0.852</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>MD Use</td>
<td>0.202</td>
<td>0.867</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Outcomes</td>
<td>0.297</td>
<td>0.147</td>
<td>0.860</td>
</tr>
<tr>
<td>4</td>
<td>Ext Motivation</td>
<td>0.168</td>
<td>0.343</td>
<td>0.228</td>
</tr>
</tbody>
</table>

Structural (Inner) Model Evaluation
Since PLS-SEM has no distributional assumptions in its parameter estimation procedure, smart PLS applies a nonparametric procedure that allows testing the statistical significance of various results. The assessment of the structural model involves examining the significance and relevance of structural model relationships (the size, $t$-statistics, and significance level of the structural path coefficients), $R^2$ values for the dependent constructs, and the predictive relevance Stone-Geisser $Q^2$ test (Hair et al., 2017).

Table 3 shows the results of the PLS-SEM analysis, including the path coefficients as well as the bootstrapped $t$-values (based on 1,000 bootstrapping runs). The results show that the structural model explains 12.2% of the variance in perceived learning outcomes. The percentage of variance explained is greater than 10%, implying satisfactory and substantive value and predictive power of the PLS model (Falk & Miller, 1992).
Intrinsic and extrinsic motivation affect perceived learning outcomes in online courses. This line of research is divided into two types of motivation: intrinsic and extrinsic. Furthermore, both types of motivation affect perceived learning outcomes positively.

Specific hypotheses ($H_1$ through $H_5$) were tested. Hypothesis 1 examined the relationship between the use of mobile devices and intrinsic motivation. The relationship was positive and significant ($\beta = .202$, $t = 3.357$). The relationship between mobile technology use and student extrinsic motivation was also significant ($\beta = .343$, $t = 6.094$), thus supporting $H_1$ and $H_2$. The effect of intrinsic motivation on learning outcome ($\beta = .261$, $t = 4.286$) was also significant, thus supporting $H_1$. Furthermore, one other hypothesis ($H_3$) was supported, meaning that a higher level of extrinsic motivation positively leads to a higher level of perceived learning outcomes. However, the effects of the use of mobile devices on perceived learning outcomes was insignificant, thus not supporting $H_4$. In summary, the findings indicated that there are strong correlations between the use of mobile devices and intrinsic motivation and between the use of mobile devices and extrinsic motivation. Furthermore, both types of motivation affect perceived learning outcomes positively.

The Stone-Geisser test of predictive relevance was also performed to further assess the model fit in the PLS analysis (Geisser, 1975; Stone, 1974). The communality $Q$-square was greater than 0 for all of the constructs, indicating that the model has predictive relevance. The blindfolding estimates are not shown due to space limitation.

### CONCLUSION AND DISCUSSIONS

The impact of the use of mobile devices on academic performance has been a subject of intense ongoing investigations over the past several decades. The majority of prior empirical research studies focused the impact of the use of mobile devices on the learning process, students’ satisfaction, and perceived learning outcomes. This research shifts the focus to the relationship between the use of mobile devices and motivation. This line of research is divided into two sections: what motivates people to use mobile devices and how mobile devices impact the students’ motivation to learn.

This empirical research investigates how the use of mobile devices influence the level of the distance learners’ motivation to learn. The major conclusions are as follows.

1. A higher level of mobile technology use in online courses is positively associated with a higher level of intrinsic and extrinsic motivation.
2. A higher level of intrinsic and extrinsic motivation in online courses is positively associated with a higher level of perceived learning outcomes.
3. A higher level of mobile technology use in online courses is not positively associated with a higher level of perceived learning outcomes.

Most mobile handheld devices are mobile phones with core functions (such as voice calls and text messaging) and mobile computing devices that support wireless communication protocols. The wireless Internet access capability of mobile technology devices transformed digital distance learning. The use of mobile devices allows students to be highly flexible in the learning process: learning at a flexible location and learning with a flexible schedule. The power of mobile digital computing and communication devices enables distance learners to learn anywhere at any time. Student learning with mobile technology integrated environments is both lifelong and lifelong learning. Mobile handheld devices allow distance learners to pursue lifelong learning, which is learning in different places (in their homes, at work, on the train, etc.) simultaneously, thanks to the ubiquity of the internet access. Lifelong learning is learning throughout one’s life time. The use of mobile devices is not required to be a life-long learner, but it will allow life-long learners more flexibility (Barnett, 2010). Further, it allows students to choose the timing and format of delivery (online, blended, and mobile) that fits their personal circumstances.
LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although this study expands our knowledge of the relationships between the use of mobile devices and the level of the intrinsic and extrinsic motivation as well as the level of the perceived learning outcomes in the context of university online learning, it has several limitations, and viable prospects for further research remain. The current research failed to confirm a positive association between mobile technology use and perceived learning outcomes without the mediating variable of the self regulation process. The dynamic nature of e-learning processes among multiple constructs, as shown in Fig. 1, was not explored but should be examined in future research. Readers are referred to (S. Eom, 2019) for a dynamic modeling. A future research agenda should examine the interdependence of the constructs influencing the perceived learning outcomes and satisfaction of e-learners. The inclusion of mediating constructs such as self-regulation learning efforts could change the third conclusion of this research.

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

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

8. In an online class like this, I prefer class material that really challenges me so I can learn new things (Int. M1).
9. In an online class like this, I prefer course material that arouse my curiosity, even if it is difficult to learn (Int. M2)
10. The most satisfying thing for me in this online class is trying to understand the content as thoroughly as possible (Int M3).
11. 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

12. Getting a good grade in this online class is the most satisfying thing for me right now (Ext. M1).
13. 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).
14. If I can, I want to get better grades in this online class than most of the other students. (Ext. M3).
15. 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).

Perceived Learning Outcomes

16. The academic quality of this online class is on par with face-to-face classes I have taken (Out1).
17. I have learned as much from this online class as I might have from a face-to-face version of the course (Out2).
18. I learn more in online classes than in face-to-face classes (Out3).
19. The quality of the learning experience in online classes is better than in face-to-face classes (Out4).

REFERENCES


