



Saudi Graduate Student Acceptance of Blended Learning Courses based upon the Unified Theory of Acceptance and use of Technology

Ali Alhramelah

King Khalid University

Hamed Alshahrani

King Khalid University

The concept of 'Blended learning' is presently one of the most widely discussed topics in education. Blended learning (BL) is a hybrid learning approach. BL combines dual or multiple teaching modals, most frequently traditional classroom learning with eLearning (Staff, 2019). This research project utilized a quantitative, non-experimental descriptive survey for the purposes of evaluating: Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) in a BL environment. The research participants were 167 graduate students in the College of Education at King Khalid University (KKU) in the City of Abha, Kingdom of Saudi Arabia. This research utilized Venkatesh et al. (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) as the primary theoretical framework. Data were collected via a self-administered online questionnaire. The hypothesized model was validated empirically using data collected from the study participants. The proposed model supports and explains up to 54% of the variance in behavioral intention to use blended learning. The research indicates that PE and EE are statistically significant predictors of behavioral intention to use blended learning. Results also show no significant effect on SI. This study contributes to the relevant body of knowledge by identifying determinants that predict students' behavioral intention to adopt and use BL. This paper also confirms that Venkatesh et al. (2003) UTAUT is a valid model for studying technology acceptance and use in education. Based on the results of this research, the authors herein present recommendations for instructional practice and future research to implement BL in academia.

Keywords: Blended learning, Venkatesh et al. (2003) UTAUT, graduate students. acceptance model, Saudi universities



INTRODUCTION

Most academics agree that using modern technologies in education can enhance student experience and knowledge (Ramakrisnan et al., 2012). Blended learning (BL) is one of the most potent and influential innovations in education because it combines the benefits of face-to-face (F2F) learning with the ‘anywhere-anytime’ power of the internet (DeSaracho, 2019). BL is widely considered one of the most important educational advances of the 21st century thus far (Thorne, 2003). BL provides learners with a direct experience in conjunction with technology-based skills that are deemed essential for success in the 21st century (Eduviews, 2009). At its most basic level, the BL approach refers to the use of online learning systems and technologies to complement and improve the conventional classroom experience. Although the concept of BL has been around since the 1960s, only recently has it become a prevalent teaching methodology integrating traditional F2F classes and online learning (DeSaracho, 2019).

Over the last few years hybrid educational models that blend traditional F2F classes with online learning have become increasingly popular (Cenejac, 2017). Dziuban et al. (2018) argued that a BL model is better than traditional F2F learning. Muawiyah et al. (2018) stated that there are several advantages to BL. The students enjoy a more engaging learning experience and benefit from the inherent flexibility of electronic course work. In addition, the researchers noted that BL can improve instructor skills. Dziuban et al. (2018) stated that 35% of higher education institutions have provided courses in BL design, and that approximately 12% of 12.2 million discrete online instruction materials are part of a blended course. Therefore, BL approach is ready to be implemented and urgently needed in higher education (Muawiyah et al., 2018).

PROBLEM STATEMENT

There is a considerable amount of research confirming that a BL approach can be successfully implemented in higher education (i.e., Brown & Diaz, 2010; Cenejac, 2017; Halverson et al., 2017; Muawiyah et al., 2018; Lopez et al., 2018; DeSaracho, 2019). However, there is little data utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) model proposed by Venkatesh et al. (2003) to address the acceptance of BL (i.e., Dakduk et al., 2018; Khechine et al., 2014). On the authors’ information and belief, there are no studies employing the UTAUT model as the framework for graduate student behavioural intentions to adopt and use BL within the Kingdom of Saudi Arabia. Anticipated student acceptance of BL is a logical prerequisite to the implementation of BL educational courses. In this research effort the authors used the Venkatesh et al. (2003) UTAUT model to analyse predictive factors of student BL acceptance in academic programs at the College of Education in King Khalid University (KKU) in Abha, Saudi Arabia. The ultimate goal of this study is to establish whether the Venkatesh et al. (2003) UTAUT model can be an outcome determinative test framework for the successful use of BL. Current literature on UTAUT is relatively thin compared to other models (Williams et al., 2014). This research study aims to enhance the theoretical foundation of blended learning using the UTAUT framework to better predict student behavioural intentions as to BL. While this research is limited to graduate students in the Kingdom of Saudi Arabia, the results will likely advance the body of BL knowledge and have predictive value of BI in other countries.



LITERATURE REVIEW

Blended Learning in Higher Education

Although blended learning emerged as a popular pedagogical concept in education at the beginning of 2000s (Güzer & Caner, 2014), the definition of BL is still somewhat ambiguous (Hrastinski, 2019). The pedagogical concept of BL can be described as a deliberate 'blending' of traditional F2F approach with technology-based learning. The purpose of BL is to stimulate and support learning (Boelens et al., 2015). Many educators regard BL only as hybrid teaching approach using in-person and online courses. The combination of methods can make the learning process more effective (Effendi, 2015). This study adopts the most commonly accepted definition of the term BL, which is a mix of traditional F2F learning and online course work (Mestan, 2019). As stated in the study by Effendi (2015), BL courses can be more interactive when employed in higher education. The BL approach has recently garnered much attention among researchers, academics, and practitioners (i.e., Cenejac, 2017; Brown & Diaz, 2010; Effendi, 2015; Serrano et al., 2019; Geng et al., 2019; Mestan, 2019; Halverson et al., 2017; Lin et al., 2017) who suggest that BL is particularly suited for higher education.

According to Cenejac (2017) both learners and teachers have generally agreed upon the efficacy of BL. A blended approach can be "less costly", is "time-saving" in nature and allows for a "more personalized ways of knowledge acquisition". Geng et al. (2019) said that BL provides "good facilitation for students' social involvement in the class" (p.1). BL adds a flexibility dimension to the traditional classroom-based instruction process (Deperlioglu & Kose, 2013). BL provides more flexibility to meet students' varying learning needs and backgrounds (Boelens et al., 2018). Rovai and Jordan (2004) conducted a study comparing three types of education graduate courses—traditional, blended, and fully online. The students in the blended courses measured highest in sense of community. Students in traditional F2F classes measured below the BL students in community, but higher than the online only participants. Parra (2013) noted that blended course students, on average, attain higher levels of achievement than both F2F and online only students.

There is some research data taken directly from King Khalid University that supports the above-stated conclusions regarding BL. Zumor et al. (2013) investigated student views on the advantages and disadvantages of BL courses using a combination of traditional F2F classes and the online learning platform 'Black Board'. The researchers found that the BL course model resulted in improvements in student English language vocabulary and student discussion board participation. The study authors attributed the improved student performance to *inter alia* the students' ability to stop, review and repeat online audio/video recordings on the Black Board platform. The authors also noted the potential benefits of students being able to practice their language skills in complete privacy, and the opportunity to communicate with the instructor and other students at varying times. The Zumor study indicates that the inherent flexibility of modern teaching technologies makes the BL method desirable in higher education. However, Zumor et al. (2013) concluded that using technology in education is not without difficulties and limitations. The researchers noted several factors detrimental to BL such as: Internet connectivity issues, hardware/software costs, hardware/software



bugs, enhanced facility requirements and significant training costs. The authors also concluded that BL can make both student and teacher performance evaluations more difficult.

Users Acceptance of Blended Learning

Over the last twenty years scholars and researchers have studied the acceptance and efficacies of new technologies in education (Fillion et al., 2012). In a study by Louho et al. (2006), the authors stated that technology acceptance "is about how people accept and adopt some technology to use" (p.15). Similarly, Dillon and Morris (1996) defined user acceptance as "the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support" (p.4). Accordingly, individuals have some degree of choice of whether to accept or to reject new technology. Lack of user acceptance has long been proven to be a restriction on the success of new technology (Gould & Lewis, 1985). Davis (1993) indicated that user acceptance is considered to be a crucial factor in determining the success or failure of a new technology.

User Intention with Blended Learning

According to Krueger and Brazeal (1994), the end-user's intention is predictive of the individual's behaviours with respect to new technologies. User "intention" is defined as a person's willingness to pursue a given behaviour and their level of commitment to achieving the target behaviour (Krueger & Brazeal, 1994). As such, understanding student intention is a critical element of implementing a BL course or program. The success or failure of BL in any given application can depend on overall desirability of the operating system(s), ease of use, and efficacy in meeting student learning expectations. The first step in any BL implementation process is to thoroughly evaluate end user attitudes and expectations in light of the course and its learning objectives.

Unified Theory of Acceptance and Use of Technology

Since the late 1980s, different models and theories of technology acceptance have been developed and tested. In 2003 Venkatesh and his colleagues integrated and unified core characteristics and elements from eight existing technology acceptance models and prominent theories. They proposed a unified model called Unified Theory of Acceptance and Use of Technology (UTAUT). The eight models Venkatesh et al. used as the basis for UTAUT included: The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995), the Diffusion of Innovation Theorem (DOI) (Rogers, 1962), the Social Cognitive Theory (SCT) (Bandura, 1986), the Motivational Model (MM) (Davis et al., 1992), and the Model of PC Utilization (MPCU) (Thompson et al., 1991).

Based on a synthesis of the above models/theories Venkatesh et al. (2003) UTAUT model explains behavioural intention to use or adapt technology using four primary determinants: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Venkatesh et al. (2003) also identified four secondary determinants that affect intention: Gender, age, willingness, and experience. The authors posit that primary determinants PE, EE, and SI influence behavioural



intention to use technology, while behavioural intention and facilitating conditions determine technology usage (Venkatesh et al., 2003).

A comprehensive literature review by Williams, et al. (2015) found that Venkatesh, et al. (2003) UTAUT model has been used to explain the adoption of various technologies in different fields. Since numerous academicians and practitioners in the field of educational technology have built their arguments on a theoretical background (i.e., Alshahrani & Walker, 2017; Bakar et al., 2013; Dakduk et al., 2018; Khechine et al., 2014; Fianu et al., 2018; Tan, 2013; Wang & Shih, 2009), it is crucial to present a theoretical framework from which academicians can analyse the user level acceptance of a BL approach. Venkatesh et al. (2003) indicated that "UTAUT is a definitive model that synthesizes what is known and provides a foundation to guide future research in this area" (p. 467). The Venkatesh et al. (2003) UTAUT model focuses on user intent and user attitudes towards information technologies, emphasizing four primary determinants of user intention and behaviour (Venkatesh et al., 2003). The Venkatesh et al. (2003) UTAUT model is widely regarded as the leading theory for explaining the adoption of technology (Williams et al., 2015). Venkatesh et al. (2003) recommended further research to examine and test the UTAUT model in different contexts and scenarios. The UTAUT model has been widely applied and tested extensively in the implementation of various technologies such as: Mobile learning (Alshahrani & Walker, 2017), information kiosks (Wang & Shih, 2009), mobile banking (Raza et al., 2019), Massive Open Online Courses (MOOCs) (Fianu et al., 2018), e-learning (Bakar et al., 2013), electronic placement tests (Tan, 2013), e-government services (Mensah, 2019), blended learning (Dakduk et al., 2018), and webinars (Khechine et al., 2014).

Mobile learning is one area which has been studied more intensively. Using the Venkatesh et al. (2003) UTAUT model as a theoretical framework, Alshahrani and Walker (2016) investigated certain factors (performance expectancy, effort expectancy, social influence) affecting students' intention to adopt and use mobile learning in higher education in Saudi Arabia. The authors utilized the same factors as those in the Venkatesh et al. (2003) study to measure all of the relevant variables. The results showed that all three of the aforementioned factors were statistically significant, positive determinants of behavioural intention to use mobile learning, with performance expectancy being the strongest predictor. The model explained 55% of the variance in student behavioural intentions to use mobile learning in Saudi Arabia. Also, in the context of mobile learning, Chao (2019) applied the Venkatesh et al. (2003) UTAUT model to investigate factors affecting students' behavioural intention as to mobile learning in higher education in Taiwan. The results from that study involving 1,562 students indicated that Behavioural Intention (BI) was significantly and positively influenced by: Satisfaction, trust, Performance Expectancy (PE), and Effort Expectancy (EE). The research model explained 47.9% of the variance in BI. The most crucial factors that influenced BI were satisfaction, PE, trust, and EE. Satisfaction and trust had direct effects on BI to use mobile learning. Also, Sun and Jeyaraj (2013) utilized the UTAUT model to evaluate the adoption of a Black Board online learning platform by students in China.

Dakduk et al. (2018) conducted another BL study based on the Venkatesh et al. (2003) UTAUT model. The researchers studied user acceptance of BL in executive education using factors including: Performance expectancy, effort expectancy, social influence,



hedonics, motivation, habit, and behavioural intention. The empirical analysis employed data from a survey of 307 in middle and senior managers in Colombia. The authors found that hedonic motivation, performance expectancy, and effort expectancy have a statistically significant positive relationship with behavioural intention to accept BL. Results also show no significant effect on SI and habits. The model explained 47% of the variance in student behavioural intentions to use BL in Colombia.

Another study based on the UTAUT framework by Khechine et al. (2014) investigated student behavioural intention to use a webinar system (Elluminate) in a blended learning course. This Canadian research surveyed 114 students. The model explained 52% of the variance in the intention to use Elluminate based on the three independent constructs (PE, SI, and FC). The authors found that the PE construct was the strongest predictor of the intention to use Elluminate.

Based on the foregoing predictive value of the Venkatesh et al. (2003) UTAUT, it is logical to investigate the determinants of BL acceptance in higher education in Saudi Arabia using the same model. Studies in the literature emphasize that Performance Expectancy (PE) (Alshahrani & Walker, 2017; Fianu et al., 2018; Venkatesh et al., 2003; Taiwo & Downe, 2013), Effort Expectancy (EE) (Alshahrani & Walker, 2016; Diño & de Guzman, 2015; Venkatesh et al., 2003), and Social Influence (SI) (Alshahrani & Walker, 2017; Taiwo & Downe, 2013; Venkatesh et al., 2003) are essential determinants in predicting behavioural intention (BI). This study applied the Venkatesh et al. (2003) UTAUT model because it explains the variance of the intention to use technologies better than other popular analytical models (i.e., TRA, TAM, and TPB) (Khechine et al., 2014, 2016). Further, Venkatesh et al. (2003) found that the UTAUT model can account for 70% of the variance in user intention. The Venkatesh et al. (2003) UTAUT model has also been validated in subsequent studies spanning a broad range of technological innovations and learning contexts. Other relevant analytical models simply have not been so rigorously tested (i.e., Alshahrani & Walker, 2017; Fianu et al., 2018; Irby & Strong, 2013; Moran et al., 2010; Venkatesh et al., 2003; Williams et al., 2009).

RESEARCH MODEL

As BL is still in its infancy in Saudi higher education, (Alebaikan, & Troudi, 2010; Alshahrani & Ward, 2014), the relative of efficacy of BL is very difficult to measure. Thus, this study attempts to measure behavioural intention (BI) as a dependent variable in the early stages of BL acceptance rather than actual usage over a longer period of time. This is consistent with other studies in places where BL is relatively new. In this type of environment student behavioural intention (BI) as to blended learning is used instead of longer-term actual usage data for predictive value. Furthermore, the higher education students in Saudi Arabia are a relatively homogeneous group. There are only small variances in student age and experience with technology. Therefore, in the research effort experience, age, gender, and willingness factors will be omitted. Venkatesh et al. (2003) found that "when both performance expectancy and effort expectancy constructs are present, facilitating conditions become non-significant in predicting intention" (p.454). Accordingly, facilitating constructs will not be taken into consideration in this study.



UTAUT CONSTRUCTS

Performance Expectancy (PE)

The first independent construct is Performance Expectancy (PE), which can be defined as "the degree to which the user expects that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). It is the first direct determinant of the behavioural intention to use a technology (Venkatesh et al., 2003). Venkatesh proposed that PE captures the constructs of perceived usefulness, extrinsic motivation, job fit, relative advantage, and outcome expectations. In the case of BL, PE refers to the level student goals can be achieved through online learning. In other words, it is students' perceived value and relative advantage that BL has on the learning experience. Existing research suggests that this is one of the most important predictors of the intention to use technology (Alshahrani & Walker, 2017; Fianu, et al., 2018; Kijisanayotin et al., 2009; Venkatesh, et al., 2003). As such, PE has received considerable research attention in different fields (i.e., Alshahrani & Walker, 2017; Dakduk et al., 2018; Venkatesh et al., 2003). Several BL studies (i.e., Chan et al., 2015; Dakduk et al., 2018) applied Venkatesh's UTAUT model to investigate factors affecting student behavioural intention to adopt and use BL in higher education. The results indicate that the Performance Expectancy (PE) was a statistically significant predictor of behavioural intention to use BL. Williams, et al. (2015) conducted a literature review about the Venkatesh et al. (2003) UTAUT model in order to evaluate the predictive power of the model. The authors reviewed the relationship between PE and BI in 116 other relevant studies. PE significantly predicted BI in 93 of the studies, indicating that PE was the strongest predictor. Likewise, Khechine et al. (2014) found that PE was the strongest predictor of the intention to use a webinar system (Elluminate) in a blended learning course based on the UTAUT model as a theoretical framework.

Effort Expectancy (EE)

Effort Expectancy (EE) can be defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p.450). The Jairak, et al. (2009) study indicated that the EE construct had a statistically significant correlative relationship with behavioural intention. In the context of BL, a few studies (i.e., Chan et al., 2015; Dakduk et al., 2018) applied the Venkatesh, et al. (2003) UTAUT model to investigate factors affecting student behavioural intention to adopt and use BL in higher education. The results indicated that the EE construct was a statistically significant predictor of behavioural intention to use BL. However, others (i.e., Bennani & Oumlil, 2014; Phichitchaisopa & Naenna, 2013) concluded that EE had no significant influence on behaviour.

Social Influence (SI)

Social Influence (SI) is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p.451). Previous research (i.e., Alaiad & Zhou, 2014; Alshahrani & Walker, 2017; Arman & Hartati, 2015; Jairak et al., 2009; Venkatesh et al., 2003) found that the SI had a significant positive effect on the behavioral intention to use, and the actual use of technology. Williams, et al. (2014), in their literature review, found that SI was the



second strongest predictor of BI, after PE. However, others (i.e., Dakduk et al., 2018) found that the effect of SI was only marginally significant.

RESEARCH QUESTION

This research study was guided by the following research question:

RQ: To what extent do performance expectancy (PE), effort expectancy (EE), and social influence (SI) predict graduate students' intention to use BL in institutions of higher education in Saudi Arabia?

HYPOTHESES

Based on previous literature research, the authors formulated the following hypotheses:

H1: Performance expectancy (PE) significantly predicts graduate students' behavioural intention (BI) to use blended learning.

H2: Effort expectancy (EE) significantly predicts graduate students' behavioural intention (BI) to use blended learning.

H3: Social influence (SI) significantly predicts graduate students' behavioural intention (BI) to use blended learning.

RESEARCH METHODOLOGY

Survey Instrument

This research study was based on data derived from a two-part, self-administered graduate student survey. The first section of the survey mainly concerned demographics and background. Participants identified basic information such as gender, age and previous BL experience. The second section of the survey queried the participating students as to their perceptions and attitudes concerning BL. The survey encompassed a total of 15 queries adopted from the original protocol by Venkatesh et al. (2003), as well as a modified version by Dakduk et al. (2018). Students answered questions based on an 'agree/disagree' response model on a 5-point rating scale: 1=Strongly Disagree; 2=Disagree; 3=Neutral; 4=Agree; and 5=Strongly Agree.

Population and Sample

This survey-based research study was designed to identify and evaluate the determinants that predict the behavioural intentions to adopt blended learning using the Venkatesh et al. (2003) UTAUT model as the framework. The research pool consisted of graduate students from the College of Education at King Khalid University (KKU) in the Kingdom of Saudi Arabia. All graduate students (both masters and doctorate level) were invited to participate in the online survey. Because this was a non-experimental study with multiple independent variables, the researchers employed a multiple linear regression (MLR) [also known simply as multiple regression] statistical technique. The authors computed the minimum sample size for this study by way of a priori statistical power analysis using G*Power (Faul et al., 2009). For the overall MLR model predicated on an alpha level established at .05, minimum power set at .80, a



moderate MLR effect size (.15) anticipated, and three predictors, the suggested minimum number of participants was ($N = 77$). After two rounds of data collection and online follow-up with the accessible population spanning 8 weeks, a total of 167 graduate students participated in the survey. All participants fully completed the survey.

RESULTS

Participant Demographic Characteristics

Highlighted demographic results from Table 1 indicate a close split between male and female respondents. Ninety survey participants (53.9 %) were male, and there were 77 females (46.1%). As to age, the largest demographic was 26-30 years old representing 48.5% of the survey population. Those older than 31 years accounted for 31.7 % of the total respondents. Students between 21- 25 years of age represented 19.8 % of the survey population. With regard to years of experience with e-learning, 43.1% of participants had used e-learning for more than six years. This may have substantially impacted their level of acceptance of blended learning. Only 3.6% of the participants had less than one year of experience with e-learning.

Table 1

Participant Demographic Characteristics

Demographic	Categories	Frequency	%
Gender	Male	90	53.9
	Female	77	46.1
Age	21- 25 years	53	31.7
	26- 30 years	81	48.5
	< 31 years	33	19.8
Experience using e-learning	Less than one year	6	3.6
	1-3 years	36	21.6
	4-6 years	53	31.7
	> 6 years	72	43.1

Reliability Analysis

Reliability is a function of “whether the research instrument is neutral in its effect and would measure the same results when used on other occasions” (Denscombe, 1998, p. 213). Because each variable [Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI)] is measured by more than one factor, the authors conducted subscale reliability analyses. When using "Likert-type scales, it is imperative to calculate and report Cronbach's alpha coefficient for internal consistency reliability for



any scales or subscales one may be using" (Gliem & Gliem, 2003, p. 88). Consequently, the researchers in this study computed Cronbach's coefficient (α) alpha on each set of items that measured the same variable. According to Kline (2011), the Cronbach's coefficient (α) alpha is "the degree to which responses are consistent across the items within a single measure" (p. 69). A reliability estimated at 0.70 or higher suggests excellent reliability; whereas predicted reliability between 0.60 and 0.70 may be acceptable, provided that other indicators of a model's construct validity are good. The Venkatesh et al. (2003) testing showed that a reliability coefficient of 0.70 or higher is acceptable for the UTAUT model. Venkatesh et al. (2003) stated that the original Cronbach Alpha as 0.90 for PE, 0.92 for EE, 0.91 for SI, and 0.88 for FC would confirm the reliability analysis of the constructs in the UTAUT model. Using the scale function of the SPSS software, the Cronbach's alpha scores (reliability coefficient) for each latent variable were computed. The scale ranges from 0 to 1. The reliability test results in the current study indicate (see Table 2), Cronbach's α is $0.901 > 0.70$ for the proffered statements, which indicates a high level of internal consistency.

Table 2

Reliability of All Items

Cronbach's Alpha	N of Items
0.901	12

The instrument had a Cronbach's Alpha measures for Performance Expectancy (PE) = 0.87, Effort Expectancy (EE) = 0.86, and Social Influence (SI) = 0.79. Therefore, the scores derived from the survey were deemed reliable as represented in Table 3.

Table 3

Reliability of Each Construct and Number of Items

Variable	Cronbach's α	N of Items
PE	0.874	4
EE	0.857	4
SI	0.788	4
* Significant at $\alpha > .70$		

Descriptive Statistics for the UTAUT Constructs

Scores from the UTAUT instrument were based on a 5-point Likert scale ranging from 1 = strongly disagree, to 5 = strongly agree. Mean composite scores were calculated for each of the following three subscales: Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI). Effort Expectancy (EE) earned the highest score ($M = 3.97$, $SD = .717$) of the constructs in the UTAUT model, and the mean was

similar to the mean scores for PE ($M = 3.87, SD = .851$). Alternatively, SI earned the lowest score ($M=3.50, SD=.852$) of the constructs in the UTAUT model (see Table 4).

Table 4

Descriptive Statistics

Variable	N	M	SD
PE	167	3.87	.851
EE	167	3.97	.717
SI	167	3.50	.852
Behavioural Intention (DV)*	167	4.15	.857

Note: DV= Dependent Variable*

Checking Assumptions

Before proceeding with the data analysis and research results, the authors herein provide information on the assumptions made in the design, execution and analysis of this research (linearity, normality).

Normality and linearity test. Data were checked for normal distribution of residuals. For inferential statistics to be conducted properly, residuals must be normally distributed. Normality of the residuals was confirmed by visual inspection of the Histogram of Standardized Residuals, and the Normal P-P Plot of the residuals are as shown in Figure 1. The analysis indicates an asymmetric bell-shaped histogram that is evenly distributed around zero, indicating that the normality assumption is likely to be accurate, as displayed in Figure 2.

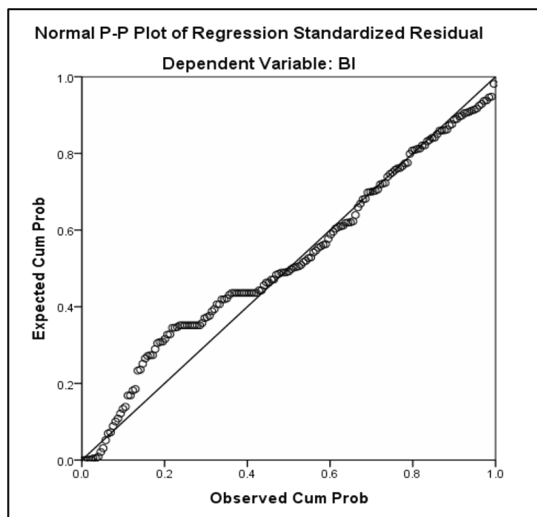


Figure 1. The normal P-P plot of the residuals standardized residuals.

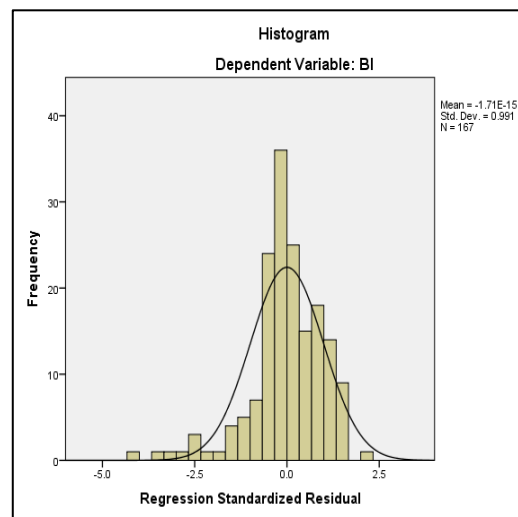


Figure 2. The histogram of



The researchers used Cook's distance statistic to determine whether an outlier data point was influential and needed to be deleted from the analysis. The rule-of-thumb values for influential outliers are 1.0 or higher for Cook's distance. In this case, the mean value of Cook's distances is (.007), which is much less than the value of 1. This means outliers do not appear to be part of the regression model.

Multiple Linear Regression (MLR) Model

Multiple Linear Regression (MLR) analysis was conducted to test if PE, EE, and SI (i.e., independent variables) predicted BI (i.e. dependent variable) to adopt blended learning. The results of the regression indicated that the omnibus model was a statistically significant predictor of the BI to use blended learning, $F= 63.117 (3, 1059)$, $p < 0.001$, R^2 equalled .537 (see Table 5). Taken as a set, the predictors (PE, EE, and SI) accounted for about 54% of the variance in the dependent variable behavioural intention (BI) to use blended learning. This result is more than acceptable for the intended purpose. The remaining 46% of the variance in BI is attributable to other determinants that were not considered in this research.

Table 5

Structural Model Evaluation and Hypothesis Testing

Model Summary									
Model	R	R ²	Adj R ²	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.733a	.537	.529	.588	.537	63.117	3	163	.000
a. Predictors: (Constant), SI, EE, PE									
b. Dependent Variable: BI									

From the correlation (See Table 6), the independent variables (EE, PE, and SI) have a positive correlation with BI. As separate predictors of BI they were all statistically correlated with respect to BI. In rank order, the results are: 1) EE (0.703), 2) PE (0.690), and 3) SI (0.387). As shown in Table 6, the results of the correlation analysis demonstrated that all of the UTAUT constructs were positively related to one other. Note that all three determinants (EE, PE, and BI) scored higher than 0.6, and showed strong positive correlations. Social Influence (SI), with coefficients in the range of 0.439 to 0.474, was positively related to the other constructs but with slightly weaker correlations.



Table 6

Correlations

		BI	PE	EE	SI
Pearson Correlation	BI	1.000	.690	.703	.387
	PE	.690	1.000	.812	.474
	EE	.703	.812	1.000	.456
	SI	.387	.474	.456	1.000
Sig. (1-tailed)	BI	.	.000	.000	.000
	PE	.000	.	.000	.000
	EE	.000	.000	.	.000
	SI	.000	.000	.000	.
N	BI	167	167	167	167
	PE	167	167	167	167
	EE	167	167	167	167
	SI	167	167	167	167

Regression coefficients.

The Beta coefficients refer to the expected change in the dependent variable (behavioural intention), per standard deviation increase in the predictor variables. Table 7 reveals that all of the Standardized Coefficients (Beta) have a positive relationship with Behavioural Intention (BI) and are statistically significant predictors. Thus, as the performance expectancy (PE) ($\beta = 0.338$) increases by one *SD* 0.857, (BI) will increase by 0.289 of a scale point (0.338×0.857 PE.SD). As Effort Expectancy ($\beta = 0.411$) increases by one *SD* 0.869, BI will increase by 0.357 (0.411×0.869 SD). As Social Influence ($\beta = 0.039$) increases by one *SD* 0.034, BI will increase by 0.106 (0.039×0.869 SI. SD).

Table 7

Regression Coefficients

Predictor	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	SE	β		
PE	.340	.094	.338	3.629	.000***
EE	.491	.110	.411	4.453	.000***
SI	.039	.061	.039	.641	.522



Note: Performance Expectancy= (PE), Effort Expectancy= (EE), Social Influence= (SI) ***Significant at $p < 0.001$ a. Dependent Variable: BI

Multiple linear regression was calculated to predict BI based on PE, EE, and SI. A significant regression equation was found ($F(3,163) = 63.117, p < 000$), with R^2 of .537. Standardized Coefficients (Beta) in the hypothesized model are included, as shown in Table 7. Two hypotheses (H1 and H2) are supported, but H3 is not supported. Note that PE ($\beta=0.338, p < 0.001$), EE ($\beta = 0.491, p < 0.001$) have positive relationships with BI of blended learning, and account for a large portion of the variance in BI ($R^2 = 0.54$). However, SI ($\beta = 0.039$) has no relationships with the BI of blended learning. Therefore, EE is the strongest predictor of the intention to use blended learning; PE is the second most important predictor, while SI is the weakest predictor. In sum, the model accounts for 54% of the variance in behavioural intention, with effort expectancy contributing more to intention than the other constructs. The summary of the hypothesis testing results is shown in Table 8. The best predictors of the model are PE and EE, $p < 0.001$. Of all the predictors, EE is the strongest predictor of behavioural intention to use blended learning.

Table 8

Summary of Hypothesis Testing Results

Hypotheses	Test Result
H ₁ : Performance Expectancy (PE) has a positive effect on Behavioural Intention (BI) to use blended learning ($\beta=.0.338$)	Supported
H ₂ : Effort Expectancy (EE) has a positive effect on Behavioural Intention (BI) to use blended learning, ($\beta = 0.491$)	Supported
H ₃ : Social Influence (SI) has a positive effect on Behavioural Intention (BI) to use blended learning, ($\beta = 0.039$)	Not Supported

DISCUSSION AND CONCLUSION

The authors herein reviewed much of the existing body of research in order to address the question raised in this paper. Previous research demonstrates that BL enhances teaching and learning in a university setting. Further, as BL is a relatively new education method, it will play an increasingly important role in higher education in the future. Note, however that BL should not be implemented into higher education programs on blind faith. University communities are very diverse. Educators must carefully evaluate the perceptions, acceptance levels and skills as to BL before making drastic changes in the learning environment. A technologically driven BL course might be a panacea in one university program, but an abject failure in another. As such, this study is limited to examining and understanding BL acceptance in higher education in the Kingdom of Saudi Arabia.



Before conducting a statistical analysis, the authors confirmed the reliability of the research data using Cronbach's alpha. All constructs are within generally accepted validity parameters. The researchers also developed a multiple regression analysis for the research study assumptions, the results of which are displayed graphically. The regression analysis indicates that all of the relevant data is satisfactory. The authors' descriptive analysis employed statistical frequency, percentage, and standard deviations to analyse respondent characteristics. A total of 167 graduate students participated in this research project, 53.9% males and 46.1% females. The researchers utilized multiple linear regression analyses to test the relationships between student intent to use blended learning and three outcome predictors: EE, PE, and SI.

This study adds to the body of knowledge on technology acceptance in that the results provide further confirmation of the validity of the Venkatesh et al. (2003) UTAUT model. In the current study, the model accounted for 54% of the variance in behavioural intention. Studies in other countries yielded similar results invariance: 52% from Canada ($N = 114$) by Khechine et al. (2014), Dakduk et al. (2018), model's effect size ($R^2 = 47\%$; $N = 307$) from Colombia, and model's effect 47.9% from Taiwan ($N = 1,562$) by Chao (2019), which illustrates the size range that is possible with this version of the UTAUT model.

This study also reveals further information regarding blended learning in higher education within the Kingdom of Saudi Arabia. The data shows that PE was a statistically significant, positive predictor of behavioural intention to use blended learning ($\beta = 0.338$, $p < 0.001$), which is congruent with findings from previous studies (i.e., Alshahrani & Walker, 2017; Dakduk et al., 2018; Fianu et al., 2018; Khechine et al., 2014; Kijisanayotin et al., 2009; Venkatesh et al., 2003; Williams et al., 2015). Further, EE was a statistically significant, positive predictor of behavioural intention to use blended learning ($\beta = 0.491$, $p < 0.001$), which is also consistent with findings from Chao (2019), Chan et al. (2015), Diño and de Guzman (2015), Dakduk et al. (2018), and Khechine et al. (2014). This result suggests that students expect blended learning curricula to be 'simple' in application and use. The data also shows that Effort expectancy (EE) is the strongest predictor of BI to use BL. This comports with the findings of previous UTAUT studies (i.e., Alshahrani & Walker, 2017; Chao, 2019; Chan et al., 2015; Diño & de Guzman, 2015; Dakduk et al., 2018; Khechine et al., 2014; Venkatesh et al., 2003). The findings obtained from the current study indicated that EE was a stronger predictor than PE. Finally, the data shows no significant evidence regarding the direction of SI on BI to adopt BL ($\beta = 0.039$, $p < 0.001$). This result supports the findings of (i.e., Dakduk et al., 2018), and is inconsistent with previous UTAUT studies (i.e., Alshahrani & Walker, 2017; Alaiad & Zhou, 2014; Arman & Hartati, 2015; Venkatesh et al., 2003; Jairak et al., 2009; Williams et al., 2014) who found that the SI determinant had a significant positive effect on the behavioural intention to use, and the actual use of technology.

This study could be valuable to decision-makers in higher education institutions. The research data is shown to be reliable and the conclusions logical. This research will add to the existing body of scientific literature about BL and technology adoption. Further, this paper might lead educators to better understand the factors that may encourage or discourage learners from applying BL in higher education. Faculty members and



administrators in the College of Education at King Khalid University and other educational institutions should use these results to in formulating strategies for using advanced technology in higher education.

IMPLICATIONS FOR PRACTICE

This study provides useful information about student behavioural intention regarding the application of BL at KKU. The results show that (graduate) students have a proclivity to BL courses. Consequently, administration and faculty members should give due consideration to expanding BL curriculum and carefully study student expectations in course design and implementation. Naturally, teaching strategies and skills will have to evolve along with BL course work. Faculty members should expect making substantial efforts to maintain core competencies in this new learning environment. Teachers will likely be required to expand their capabilities in course design and delivery through special training courses about online curriculum. Managers will have to provide the tools required for teachers and students to succeed. The increasing use of BL will require updated physical infrastructure, equipment, software and training required for BL course design and implementation. Note that this effort might apply not just to the College of Education; BL could be adopted by all colleges within the university system.

Graduate students at King Khalid University College of Education can benefit from a BL approach to higher education. Students who must travel great distances to campus will obviously save time and commuting costs. Also, online courses facilitate communications between teacher and student. Technology (i.e. email, university platform) allows for communications more frequently and at irregular hours. BL also allows for students to interact and corroborate on course work more easily. In addition, online learning management systems (i.e. BlackBoard) can improve productivity and improve the quality of education.

LIMITATIONS AND SUGGESTED FURTHER RESEARCH

There are some inherent limitations and biases in this study. The research was limited to graduate students in one college, within a single university system in the Kingdom of Saudi Arabia. Also, the research participants completed the survey in the Arabic language, which was translated back into English. Some accuracy might have been lost in translation. In addition, the authors did not examine actual technology usage (i.e., behaviour use). By employing the UTAUT model, the researchers predicted student behaviour by way of perceptual, behavioural intention. The research was based on a self-administered, online survey, and there was no triangulation of data sources.

Notwithstanding the limited scope of the research participant pool, the authors posit that the results should be considered material to and representative of student behaviour in other graduate programs and other universities in Saudi Arabia. As a group, students in the Kingdom are relatively homogeneous in many significant ways. The vast majority share a common: Ethnicity, culture, religion and educational background. Moreover, educational programs across universities are fairly uniform in nature. The national government controls broad educational policy, so there is no diversity of



agenda on higher education. Execution of educational policies falls exclusively under the jurisdiction of the national Ministry of Education. While there are differences in implementation, program goals and objectives for each major are uniform throughout the country. As the students and their educational programs are similar, it is logical to assume that the results of this study very likely yield comparable results.

Naturally, the authors herein would like to add to the relevant body of knowledge and provide other academics with a platform for further research on the topic. This research project, and the conclusions set forth herein, are limited to the Kingdom of Saudi Arabia. One worthwhile endeavour would be to test the results in other countries, cultures and educational settings. This would provide deeper insight as to broader societal norms and trends on the subject of BL. This could lead to major improvements in education at many levels. This research paper is instructive on essential BL issues that have not been addressed in previous UTAUT- based studies. Hence, the proposed model is a significant contribution to the emerging literature on BL. To further advance knowledge on the subject, the authors of this study suggest repeating the research in a variety of geographical locations and diverse institutions.

Acknowledgement.

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

References

- Adhikari, J., Mathrani, A., & Scogings, C. (2017). A longitudinal journey with BYOD classrooms: issues of access, capability and outcome divides. *Australasian Journal of Information Systems*, 21. <https://doi.org/DOI:10.3127/ajis.v21i0.1693>
- Argueta, R., Huff, J., Tingen, J., & Corn, J. (2011). Laptop initiatives: summary of research across seven states. *Friday Institute for Educational Innovation North Carolina University*. <https://www.fi.ncsu.edu/wpcontent/uploads/2013/05/laptop-initiatives-summary-ofresearch-across-seven-states.pdf>
- Australian Bureau of Statistics. (2018). *8146.0 - Household use of information technology, Australia, 2016-17*. Retrieved 30 May from <https://www.abs.gov.au/ausstats/abs@.nsf/0/ACC2D18CC958BC7BCA2568A9001393AE?Opendocument>
- Bertram, A., & Waldrip, B. (2013). ICT for ICT's sake: secondary teachers' views on technology as a tool for teaching and learning. *Australian Educational Computing*, 28(1). <http://journal.acce.edu.au/index.php/AEC/article/view/9>
- Bourdieu, P. (2002). The forms of capital. In N. W. Biggart (Ed.), *Readings in economic sociology* (pp. 280-291). Blackwell Publishers.



- Camerini, A. L., Schulz, P. J., & Jeannet, A. M. (2018). The social inequalities of internet access, its use, and the impact on children's academic performance: evidence from a longitudinal study in Switzerland. *new media & society*, 20(7), 2489-2508. <https://doi.org/https://doi.org/10.1177/1461444817725918>
- Crook, S. J., Sharma, M. D., & Wilson, R. (2015). An evaluation of the impact of 1:1 laptops on student attainment in senior high school sciences. *International Journal of Science Education*, 37(2), 272-293. <https://doi.org/10.1080/09500693.2014.982229>
- Digital Education Advisory Group. (2012). *Beyond the classroom: a new digital education for young Australians in the 21st century*. Australian Department of Education and Employment. https://docs.education.gov.au/system/files/doc/other/deag_final_report.pdf
- DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital inequality: from unequal access to differentiated use. In *Social Inequality* (pp. 355-400). Russell Sage Foundation.
- Dolan, J. E. (2016). Splicing the Divide: A Review of Research on the Evolving Digital Divide Among K–12 Students. *Journal of Research on Technology in Education*, 48(1), 16-37. <https://doi.org/https://doi.org/10.1080/15391523.2015.1103147>
- Duffy, C. (2020). *Eight big issues for vulnerable students highlighted by coronavirus crisis, charity says*. ABC News. Retrieved 25 May from <https://www.abc.net.au/news/2020-05-25/coronavirus-students-back-to-school-education-digital-divide/12273772>
- Dunleavy, M., & Heinecke, W. F. (2007). The impact of 1:1 laptop use on middle school math and science standardized test scores. *Computers in the Schools*, 24(3-4), 7-22. https://doi.org/https://doi.org/10.1300/J025v24n03_02
- Fluck, A. E. (2011). Laptop Classes in Some Australian Government Primary Schools. *Australian Educational Computing*, 26(1), 10-15. https://acce.edu.au/past-issues/#elf_11_Lw
- Fraillon, J., Ainley, J., Schulz, W., Friedman, T., & Duckworth, D. (2019). *Preparing for life in a digital world: the IEA international computer and information literacy study 2018 international report*. International Association for the Evaluation of Educational Achievement. https://research.acer.edu.au/ict_literacy/23/
- Fraillon, J., Gebhardt, E., Friedman, T., Duckworth, D., O'Malley, K., & Vernon, K. (2018). *NAP sample assessment ICT literacy; years 6 and 10*. Australian Curriculum Assessment and Reporting Authority. https://www.nap.edu.au/docs/default-source/default-document-library/2017napictlreport_final.pdf?sfvrsn=2



- Gomez, D. (2018). The three levels of the digital divide: barriers in access, use and utility of internet among young people in Spain. *Interacoes: Sociedade E As Novas Modernidades*, 34, 34-91.
<https://doi.org/https://doi.org/10.31211/interacoes.n34.2018.a4>
- Gomez, D. (2019). Technological capital and digital divide among young people: an intersectional approach. *Journal of Youth Studies*, 22(7), 941-958.
<https://doi.org/10.1080/13676261.2018.1559283>
- Hargittai, E. (2002). Second-level digital divide: differences in people's online skills. *First Monday*, 7(4). <https://doi.org/https://doi.org/10.5210/fm.v7i4.942>
- Harper, B., & Milman, N. B. (2016, 2016/04/02). One-to-one technology in k-12 classrooms: a review of the literature from 2004 through 2014. *Journal of Research on Technology in Education*, 48(2), 129-142.
<https://doi.org/https://doi.org/10.1080/15391523.2016.1146564>
- Helsper, E., J. (2012). A corresponding fields model for the links between social and digital exclusion. *Communication Theory*, 22(4), 403-426.
<https://doi.org/https://doi.org/10.1111/j.1468-2885.2012.01416.x>
- Helsper, E. J., & Reisdorf, B. C. (2017). The emergence of a “digital underclass” in Great Britain and Sweden: changing reasons for digital exclusion. *new media & society*, 19(8), 1253-1270. <https://doi.org/10.1177/1461444816634676>
- Islam, M. S., & Grönlund, Å. (2016, 2016/05/01). An international literature review of 1:1 computing in schools. *Journal of Educational Change*, 17(2), 191-222.
<https://doi.org/https://doi.org/10.1007/s10833-016-9271-y>
- Janssen, K., & Phillipson, S. (2015). Are we ready for BYOD? A systematic review of the implementation and communication of BYOD programs in Australian schools. *Australian Educational Computing*, 30(2).
<http://journal.acce.edu.au/index.php/AEC/article/view/54>
- Kposowa, A. J., & Valdez, A. D. (2013). Student laptop use and scores on standardized tests. *Journal of Educational Computing Research*, 48(3), 345-379. <https://doi.org/https://doi.org/10.2190/EC.48.3.d>
- Lowther, D. L., Inan, F. A., Strahl, J. D., & Ross, S. M. (2012). Do one-to-one initiatives bridge the way to 21st century knowledge and skills? *Journal of Educational Computing Research*, 46(1), 1-30.
<https://doi.org/https://doi.org/10.2190/EC.46.1.a>
- Moon, U. J., & Hofferth, S. (2018). Change in Computer Access and the Academic Achievement of Immigrant Children. *Teachers College Record*, 120(4).



- Napoli, P. M., & Obar, J. A. (2014). The emerging mobile internet underclass: a critique of mobile internet access. *The Information Society*, 30(5), 323-334. <https://doi.org/10.1080/01972243.2014.944726>
- Nash, V., & Eynon, R. (2020). Coronavirus school closures impact 1.3 billion children - and remote learning is increasing inequality. *The Conversation*. Retrieved 20 May, from <https://theconversation.com/coronavirus-school-closures-impact-1-3-billion-children-and-remote-learning-is-increasing-inequality-138656>
- OECD. (2010). *Are the new millennium learners making the grade? Technology use and educational performance in PISA 2006*. OECD Publishing. <https://doi.org/doi:https://doi.org/10.1787/9789264076044-en>
- Orwell, G. (1945). *Animal Farm*. Penguin Books.
- Penuel, W. R. (2006). Implementation and effects of one-to-one computing initiatives: a research synthesis. *Journal of Research on Technology in Education*, 38(3), 329-348. <https://doi.org/https://doi.org/10.1080/15391523.2006.10782463>
- Pullen, D. (2015). The influence of the home learning environment on middle school students' use of ICT at school. *Australian Educational Computing*, 30(1). <http://journal.acce.edu.au/index.php/AEC/article/view/49>
- Ragnedda, M. (2018). Conceptualizing digital capital. *Telematics and Informatics*, 35(8), 2366-2375. <https://doi.org/https://doi.org/10.1016/j.tele.2018.10.006>
- Ragnedda, M., & Mutsvairo, B. (2018). Digital inclusion: empowering people through information and communication technologies (ICTs). In M. Ragnedda & B. Mutsvairo (Eds.), *Digital Inclusion. An International Comparative Analyses* (pp. 7-14). Lexington Book. <http://hdl.handle.net/10453/128561>
- Ragnedda, M., Ruiu, M. L., & Addeo, F. (2019). Measuring digital capital: an empirical investigation. *new media & society*, 22(5), 793-816. <https://doi.org/https://doi.org/10.1177/1461444819869604>
- Reisdorf, B. C., Fernandez, L., Hampton, K. N., Shin, I., & Dutton, W. H. (2020). Mobile phones will not eliminate digital and social divides: how variation in internet activities mediates the relationship between type of internet access and local social capital in Detroit. *Social Science Computer Review*, 1-21. <https://doi.org/https://doi.org/10.1177/0894439320909446>
- Resta, P., & Laferrière, T. (2015). Digital equity and intercultural education. *Education and Information Technologies*, 20(4), 743-756. <https://doi.org/http://dx.doi.org/10.1007/s10639-015-9419-z>



- Resta, P., Laferrière, T., McLaughlin, R., & Kouraogo, A. (2018). Issues and challenges related to digital equity: an overview. In *Second international handbook of information technology in primary and secondary education*. Cham: Springer. https://doi.org/https://doi.org/10.1007/978-3-319-71054-9_67
- Rogers, E. M. (2003). *Diffusion of Innovations Fifth Edition*. The Free Press, Simon & Schuster, Inc.
- Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *new media & society*, 6(3), 341-362. <https://doi.org/10.1177/1461444804042519>
- Selwyn, N. (2019). *Digital lessons? Public opinions on the use of digital technologies in Australian schools*. <https://pdfs.semanticscholar.org/c497/35bd0ebfd5427e965ea79caed127b916d5c2.pdf>
- Selwyn, N., & Facer, K. (2014). The sociology of education and digital technology: past, present and future. *Oxford Review of Education*, 40(4), 482-496. <https://doi.org/https://doi.org/10.1080/03054985.2014.933005>
- Selwyn, N., Nemorin, S., Bulfin, S., & Johnson, N. F. (2017). Left to their own devices: the everyday realities of one-to-one classrooms. *Oxford Review of Education*, 43(3), 289-310. <https://doi.org/https://doi.org/10.1080/03054985.2017.1305047>
- Shapley, K., Sheehan, D., Maloney, C., & Caranikas-Walker, F. (2011, 09//). Effects of technology immersion on middle school students' learning opportunities and achievement [Article]. *Journal of Educational Research*, 104(5), 299. <https://doi.org/https://doi.org/10.1080/00220671003767615>
- Smith, J., Skrbis, Z., & Western, M. (2013). Beneath the 'digital native' myth: understanding young Australians' online time use. *Journal of Sociology*, 49(1), 97-118. <https://doi.org/10.1177/1440783311434856>
- Thomson, S. (2020). What PISA tells us about our preparedness for remote learning. *Teacher*. <https://www.teachermagazine.com.au/columnists/sue-thomson/what-pisa-tells-us-about-our-preparedness-for-remote-learning>
- Tondeur, J., Sinnaeve, I., Van Houtte, M., & van Braak, J. (2010). ICT as cultural capital: the relationship between socioeconomic status and the computer-use profile of young people. *new media & society*, 13(1), 151-168. <https://doi.org/https://doi.org/10.1177/1461444810369245>
- van Deursen, A., Helsper, E. J., Eynon, R., & van Dijk, J. (2017). The compoundness and sequentiality of digital inequality *International Journal of Communication*, 11, 452-473. <http://ijoc.org/index.php/ijoc/index>



- van Deursen, A., & van Dijk, J. (2010). Internet skills and the digital divide. *New Media and Society*, 13(6), 893-911.
<https://doi.org/10.1177/1461444810386774>
- van Deursen, A. J., & Helsper, E. J. (2015). The third-level digital divide: who benefits most from being online? *Studies in Media and Communications*, 10, 29-52. <https://doi.org/https://doi.org/10.1108/S2050-206020150000010002>
- van Deursen, A. J., & van Dijk, J. A. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *New Media & Society*, 21(2), 354-375. <https://doi.org/10.1177/1461444818797082>
- van Dijk, J. (2002). A framework for digital divide research. *The Electronic Journal of Communication*, 12(1), 7.
<http://www.cios.org/EJCPUBLIC/012/1/01211.html>
- van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics*, 34(4), 221-235.
<https://doi.org/https://doi.org/10.1016/j.poetic.2006.05.004>
- Wang, L., & Liu, C. (2017). The mobile internet underclass: reality or hyperbole? *Journal of Information Science*, 44(5), 569-579.
<https://doi.org/https://doi.org/10.1177/0165551517690083>
- Warschauer, M., Zheng, B., Niiya, M., Cotten, S., & Farkas, G. (2014). Balancing the one-to-one equation: equity and access in three laptop programs. *Equity & Excellence in Education*, 47(1), 46-62.
<https://doi.org/https://doi.org/10.1080/10665684.2014.866871>
- Yuen, A. H. K., Park, J., Chen, L., & Cheng, M. (2018). The significance of cultural capital and parental mediation for digital inequity. *new media & society*, 20(2), 599-617. <https://doi.org/10.1177/1461444816667084>
- Zheng, B., Warschauer, M., Lin, C.-H., & Chang, C. (2016). Learning in one-to-one laptop environments: a meta-analysis and research synthesis. *Review of Educational Research*, 86(4), 1052-1084.
<https://doi.org/10.3102/0034654316628645>
- Zilka, G. C. (2016). Reducing the digital divide among children who received desktop or hybrid computers for the home. *Journal of Information Technology Education: Research*, 15, 233-251.
<https://doi.org/https://doi.org/10.28945/3519>