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Exploring High School Students' Educational Use of YouTube

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Abstract

YouTube is one of the most prevalent social media sites across the globe. However, there is a lack of research on factors influencing educational use of YouTube. This study examines high school students' educational use of YouTube with unified theory of acceptance and use of technology (UTAUT). Using structural equation modeling, the proposed model is tested. Results demonstrate that performance expectancy and social influence are the significant predictors of behavioral intention to use YouTube. Furthermore, behavioral intention is the significant predictor of actual usage. The results suggest that students intend to use YouTube for improving their academic performance. Social influence also contributes to their intention. Based on previous literature, the results are discussed.

Keywords: YouTube, high school students, unified theory of acceptance and use of technology (UTAUT), structural equation model

Introduction

Information and communication technologies (ICTs) are one of the most prominent integral assets of contemporary education. Teaching and learning activities that incorporate different digital devices and platforms are becoming more prevalent, such as using YouTube for educational purposes (Jung & Lee, 2015; Terlemez, 2016). First released in 2005, YouTube has become the world's largest online video platform in which users can upload, share, watch, and discuss video clips across the globe (Lin & Polaniecki, 2009). Youth frequently spend their time on digital media (Erstad, 2012; Ünlüsoy, de Haan, Leander, & Volker, 2013); according to the Pew Internet and American Life Project (Madden, 2009), 89% of 18-29-year-olds use online video platforms like YouTube, with 36% of them watching movies or educational videos on a daily basis.

Numerous studies emphasize that videos have an inherent instructional affordance for teaching and learning processes. For instance, Adhikari, Sharma, Arjyal, and Uprety (2016) posited that YouTube is a widely used source of information, and that when quality videos are posted by professional organizations and governments, they can add value by providing detailed and accurate information. Bonk (2008) suggested that online video content may help students increase their grasp of educational concepts and arouse an overall interest in learning.

The existing literature emphasizes the value and importance of the use and potential of YouTube as an educational source of information (Jung & Lee, 2015; Terlemez, 2016). However, there is a lack of research on high school students' educational use of YouTube. This study examines the factors influencing the educational use of YouTube by high school students in Turkey with unified theory of acceptance and use of technology (UTAUT).

Theoretical Background

There are various theoretical models available to assist practitioners in understanding the factors that might influence a student's acceptance and use of technology. In this study, factors influencing students' acceptance and use of YouTube for educational purposes were drawn from the unified theory of acceptance and use of technology (UTAUT) proposed by Venkatesh, Morris, Davis, and Davis (2003). There are four pivotal constructs in UTAUT (performance expectancy, effort expectancy, social influence, and facilitating conditions) along with four moderators (gender, age, experience, and voluntariness). Venkatesh, Thong, and Xu (2012) extended the original model by proposing UTAUT2, which included three more constructs; namely, price value, hedonic motivation, and habit. Venkatesh, Thong, and Xu (2016) analyzed UTAUT and its extensions by suggesting a multi-level framework to further refine the explanatory power of the model. In the context of this study, the four core constructs; namely, performance expectancy, effort expectancy, social influence, and facilitating conditions, were drawn to understand students' educational use of YouTube.

Previous studies tested UTAUT for various user behavior with different participants and different technological features, for example, interactive whiteboards (Šumak & Šorgo, 2016; Wong, Teo, & Goh, 2015), e-learning systems (El-Masri & Tarhini, 2017; Ngampornchai & Adams, 2016) and mobile learning (Abu-Al-Aish & Love, 2013; Hao, Dennen, & Mei, 2017). The existing literature demonstrates that UTAUT is being validated to explain and predict behavioral intention and user behavior concerning technology acceptance. However, Venkatesh et al. (2012) suggested that it is important to test UTAUT within different cultures, technological features, and settings, since factors influencing the adoption of a technology might vary with respect to different cultural backgrounds, technological features, and target populations. In this regard, it is conceivable to expect and accept that the factors influencing students' educational use of YouTube might differ from general information systems usage contexts.

Given the importance of exploring possible factors that might influence a student's acceptance and use of YouTube for educational purposes, and the need to extend theories and models of technology adoption to new contexts to advance generalizability and applicability, this study investigated the determinants of the educational use of YouTube in the margin of UTAUT.

The Study

Previous research suggests that UTAUT is one of the rigorous models that explains determinants of technology use (e.g., Ngampornchai & Adams, 2016; Nistor, Göğüş, & Lerche, 2013). Using UTAUT, this study examines determinants of high school students' educational use of YouTube. Figure 1 illustrates the research model and the predictors of educational use of YouTube. As it is indicated in Figure 1 below, performance expectancy (PE), effort expectancy (EE), and social influence (SI) are determinants of behavioral intention (BI) to use YouTube. Behavioral intention and facilitating conditions (FC) are the determinants of the actual usage. Each predictor is explained under the subsequent sections.

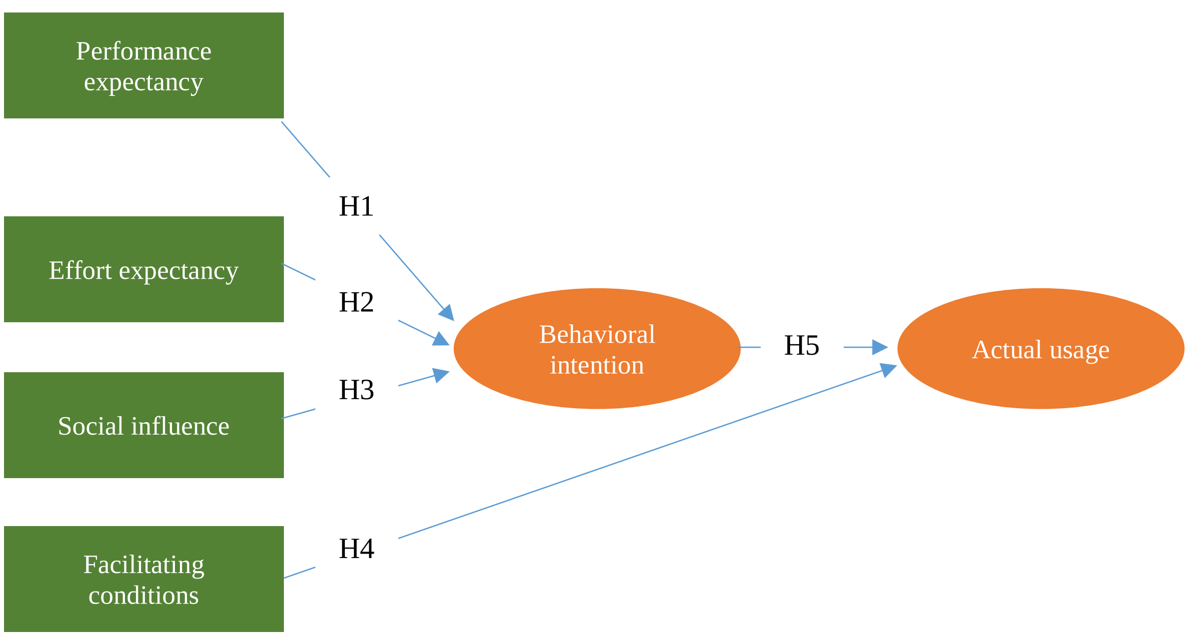

Figure 1. The research model and hypothesis for predicting high school students' educational use of YouTube.

Performance Expectancy

Performance expectancy (PE) is defined as “the degree to which an individual believes that using the system will help him or her to attain gains in job performance” (Venkatesh et al., 2003, p. 447). UTAUT postulated PE as one of the direct determinants of behavioral intention (BI) to use technology. Detailed information about BI is provided after facilitating conditions. There are numerous studies that validated PE as a significant determinant of BI, for instance, El-Masri and Tarhini (2017) examined the e-learning adoption with university students from Qatar and the USA. They found that in both samples, PE was one of the significant predictors of BI. Similarly, Jung and Lee (2015) investigated factors influencing university students’ and educators’ YouTube acceptance with UTAUT. They found that PE had a significant positive effect on BI for both groups. In this study, PE was conceptualized as students’ perceptions concerning the potential benefits of using YouTube for educational purposes. In accordance with previous studies on UTAUT, this study postulated that if students perceive YouTube as useful and might add value to their educational experience, then they will be more likely to adopt it. On the other hand, if they are more skeptical regarding the educational value of YouTube, then they are more resistant to adopt it. Therefore, this study proposed the following hypothesis:

> H1: Performance expectancy is a significant predictor of students’ behavioral intention to use YouTube for educational purposes.

Effort Expectancy

Effort expectancy (EE) is defined as “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, p. 450). UTAUT proposed that EE is one of the direct determinants of BI. Many studies reported that EE is a significant determinant of BI. For instance, Teo and Noyes (2014) examined pre-service teachers’ self-reported intentions to use information technology by UTAUT. They found that EE was a significant determinant of BI to use information technology. Similarly, Ngampornchai and Adams (2016) carried out a study to investigate undergraduate students’ readiness for online learning within the margin of UTAUT along with extending the model with multiple variables. The researchers found that EE had a strong positive relationship and strong indicator of technology acceptance. In accordance with existing studies on UTAUT, this study included EE to investigate students’ perceptions of whether the use of YouTube for educational purposes is free of effort and to predict BI. In other words, EE is conceptualized as the degree of ease associated with the use of YouTube for educational purposes. It is proposed that if students think that YouTube is easy to use for educational purposes, then they are more likely to adopt it. Therefore, this study postulated the following hypothesis:

> H2: Effort expectancy is a significant predictor of students’ behavioral intention to use YouTube for educational purposes.

Social Influence

Social influence (SI) is defined as “the degree to which an individual perceives that important others believe he or she should use the system” (Venkatesh et al., 2003, p. 451). According to El-Masri and Tarhini (2017), the reason why SI is a direct determinant of BI is the fact that people might be influenced by others’ ideas and might involve in certain action even if they do not want to. SI is emphasized to have different effect size on BI with respect to different cultural backgrounds, particularly in collectivist cultures (e.g., Venkatesh & Zhang, 2010). There are numerous studies validated that SI is one of the direct determinants of BI (e.g., Hao et al., 2017; Im, Hong, & Kang, 2011). Venkatesh et al. (2003) argued that SI is not a significant predictor of BI in voluntary or utilitarian contexts, yet it becomes significant in case of a mandatory setting. Although students' behavioral intention to use YouTube for educational purposes is a case of voluntary use of technology, this study tested direct effect of SI on BI. In the context of this study, students will be more likely to adopt YouTube for educational purposes if it is valued by one's social environment or by important others, such as, family members, friends, or teachers. Hence, the following hypothesis was proposed:

> H3: Social influence is a significant predictor of students' behavioral intention to use YouTube for educational purposes.

Facilitating Conditions

Facilitating conditions (FC) are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). This study conceptualized FC as students' perceptions on whether they have access to required resources and necessary support to use YouTube for educational purposes. In fact, FC is not proposed as a direct determinant of BI in the original UTAUT model (see Venkatesh et al., 2016). However, previous studies investigated FC in several different ways as context, participants, and technological features vary within these studies (e.g., Lin, Zimmer, & Lee, 2013; Wong, 2016). For instance, Wong (2016) investigated primary school teachers' use of education technology in Hong Kong and found that FC is a strong dominating factor compared to perceived ease of use and perceived usefulness. This study included FC to propose that students will be more likely to adopt YouTube for educational purposes if they have access to required resources and necessary support. Hence, this study postulated the following hypothesis:

> H4: Facilitating conditions is a significant predictor of students' actual usage of YouTube for educational purposes.

Behavioral Intention to Use YouTube

According to Ajzen (1991) "intentions are assumed to capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior" (p. 181). BI is determined as a proxy factor for users' acceptance and use of a technology (e.g., Venkatesh et al., 2003; Venkatesh et al., 2012). In the context of this study, BI measures high school students' preferences and intentions toward the use of YouTube for educational purposes. UTAUT postulated that BI is a significant predictor of actual usage of a technology. In this regard, a hypothesis was tested on whether BI is a significant determinant of actual use of YouTube.

> H5: Behavioral intention is a significant predictor of students' actual usage of YouTube.

Based on previous studies and developed hypotheses, the research model was proposed as illustrated in Figure 1. High school students' behavioral intention toward the use of YouTube for educational purposes is determined by subsequent factors as in the UTAUT.

Method

To be able to examine the research model, the study used a survey design, which included demographic information and items related to educational use of YouTube. The items were adapted from existing scales previously validated (e.g., Venkatesh et al., 2003). Structural equation modeling (SEM) approach was underpinned to verify the associations between the indigenous (BI and AU) and exogenous (PE, EE, SI, and FC) constructs. In this regard, stages for employing SEM were followed as suggested by Schreiber, Nora, Stage, Barlow, and King (2006). The pre-analysis stage of SEM includes the reporting of sample size, normality, outliers, linearity, multicollinearity, software program, and estimation method. The statistical analysis was carried out in IBM SPSS Statistics 22 and LISREL v.8.71 and the maximum likelihood estimation method was performed to test the associations between indigenous and exogenous relationships.

First, missing data (n = 32) were discarded from the data set. These included items that had more than one response to 5-point Likert scale and no response to survey items related to measuring participants' educational use of YouTube (Çokluk, Şekercioğlu, & Büyüköztürk, 2016). This resulted in data collected from 367 participants. Second, using z scores that are outside of the range of ± 3 (n = 32) were discarded from the data set, as well (Çokluk et al., 2016). This resulted in a data set that is collected from 335 participants. Third, the sample size (n = 335) is above the threshold to conduct SEM (Hair, Black, Babin, Anderson, & Tatham, 2006; Hoe, 2008). Fourth, the normality of the data set was tested using skewness, kurtosis, and linearity values. The skewness (ranged from -1.388 to 0.381) of the data was in the range of ± 3 and satisfied the recommended threshold (Kline, 2005). The kurtosis of the data (ranged from -0.933 to 1.954) was in the range of ± 10 and satisfied the recommended threshold (Klein, 2005). The linearity ranged from 0.079 to 0.824 that are bigger than 0.05. This also satisfied the recommended threshold value for the linearity of the data. Finally, the multicollinearity of the data is tested using the variable inflation factor (VIF). The multicollinearity values were smaller than 3.0 (ranged from 1.024 to 2.839) and satisfied the recommended threshold (O'Brien, 2007). These values suggest that the data is appropriate to test SEM.

Measurements

This study underpinned the process of preparing and administering a survey instrument. The items used to collect the data from high school students were drawn from previous studies that are published both in English and Turkish (e.g., Venkatesh et al., 2003; Venkatesh et al., 2012). Using previously validated items enabled an extent of content and face validity. Furthermore, three experts from the field of educational sciences and six experts from the field of educational technology provided feedback concerning the content and face validity. Based on experts' suggestions, slight modifications were completed in order to satisfy the content and face validity of the survey instrument. Specifically, along with demographics, the survey instrument included 22 items in total: performance expectancy (PE - 5 items), effort expectancy (EE - 3 items), social influence (SI - 4 items), facilitating conditions (FC - 4 items), behavioral intention (BI - 3 items), and actual usage (AU - 3 items). The items were anchored on a 5-point Likert-scale ranging from "1 - strongly disagree" to "5 - strongly agree."

Factor Structure

The data set were controlled for the suitability of factor analysis. Kaiser-Meyer-Olkin (KMO) tests and Bartlett's test of sphericity were used as a measure of sampling adequacy. The results show that KMO values ranged between 0.605 and 0.892, which was above the recommended threshold value of .50 (Kaiser, 1974). Bartlett's test of sphericity also ensured that the constructs were independent. Table 1 illustrates the results that verified the appropriateness of data for factorability. These results suggested testing the data for exploratory factor analysis using principal components extraction. Operationalization of a unidimensional solution for each construct appeared to be the most appropriate measurement based on the scree-plot eigenvalues.

Table 1

Suitability of the Data for Factor Analysis

Constructs	KMO	Chi-Square	Sig.
PE	0.892	1,218.837	0.000
EE	0.605	188.139	0.000
SI	0.794	509.838	0.000
FC	0.708	358.047	0.000
BI	0.755	658.583	0.000
AU	0.758	798.182	0.000

Participants and Procedures

A total of 399 high school students were recruited through convenience sampling method. Table 2 illustrates the demographic information about the participants of the study. Missing values and outliers were discarded from statistical analyses. The statistical analyses were employed with data collected from 335 responses. As it is illustrated in Table 2, there were 178 (53,1%) female and 157 (46,9%) male participants. The age of the participants ranged from 14 to 19 (Mean = 16.21, *SD* = 1.217) and the majority of the participants reported that they have a mobile phone (304, 90.7%). Furthermore, 298 (89.0%) of the participants had Internet access over their mobile phones. This demographic information illustrates a point concerning the accessibility of mobile technology by the majority of the respondents. While the daily average Internet usage was 4 hours, the participants indicated that they spend 1 hour on the Internet for educational purposes on a daily basis. The demographic information as indicated in Table 2 also provided a ground for further discussion about how participants' characteristics may contribute to associations between the constructs.

Table 2

Demographics of the Participants

	Frequency	%
Gender		
Female	178	53.1
Male	157	46.9
Total	335	100.0

*Age**		
Mean	16.21	
Standard deviation	1.217	
Minimum	14	
Maximum	19	
Mobile phone ownership	304	90.7
Internet access from the mobile phone*	298	89.0
Daily average Internet usage (hours)*	4	
Daily average Internet usage for educational purposes (hours)*	1	

*Has a missing value.

Results

Descriptive Statistics

The descriptive statistics of the constructs (PE, EE, SI, FC, BI, AU) are illustrated in Table 3. The mean values of the constructs on a 1-to-5 scale ranged from 2,2918 (SI; *SD* = 0,99987) to 4,3940 (EE, *SD* = 0,63756).

Table 3

Descriptive Statistics, Skewness, and Kurtosis Values for Normality Assumptions of SEM

Constructs	Item	Mean	Standard deviation	Skewness	Kurtosis
PE	5	3.0794	1.12203	-0.081	-0.872
EE	3	4.3940	0.63756	-1.088	0.641
SI	4	2.2918	0.99987	0.381	-0.678
FC	4	4.4881	0.56422	-1.388	1.954
BI	3	3.4199	1.23063	-0.362	-0.933
AU	3	3.0408	1.16873	-0.005	-0.867

As it is indicated in Table 3, the normal distribution of the data was satisfied with the kurtosis and skewness values. The standard kurtosis value was smaller than 10 (ranged from -0.678 to 1.954) and the standard skewness value was smaller than 3 (ranged from -1.388 to 0.381; Kline, 2005). These values suggest that the data is appropriate to use structural equation modeling for testing associations between the constructs.

Convergent Validity

To test the convergent validity of the measurement items under each construct, three conditions as suggested by Fornell and Larcker (1981) were investigated. These three conditions are: (1) the item reliability of each construct, (2) the composite reliability of each construct, and (3) the average variance extracted (AVE). According to Hair et al. (2006), the factor loadings should be higher than .50, the composite reliability should exceed 0.60, and AVE should be higher than 0.50. As illustrated in Table 4, the factor loadings of each item were higher than 0.50 except FC19, which has a factor loading of 0.353. Since it is also at an acceptable level (Hair et al., 2006) the authors did not leave the item. The composite reliability exceeds the threshold value of 0.60, and the value of AVE was also higher than the recommended value of 0.30. Hence, the three conditions for convergent validity were satisfied. In addition to these three conditions, Cronbach's alpha values were also reported. As it is provided in Table 4, it ranged between 0.58 and 0.93. From Table 4, all the measures fulfill the recommended threshold values and indicates that the convergent validity for the measurement items and constructs are validated.

Table 4

Convergent Validity of the Constructs

Items	Factor loads	CR	AVE %	Cronbach's alpha
AU				
1. I follow instruction about my courses on YouTube.	0.920			
2. I use YouTube to learn about my courses.	0.940	0.95	0.87	0.93
3. I watch videos about my courses on YouTube.	0.944			
PE				
4. YouTube makes it easy to understand my courses.	0.903			
5. YouTube helps me to become more successful in my courses.	0.917			
6. I learn more quickly using YouTube.	0.865	0.94	0.76	0.92
7. I find using YouTube for educational purposes useful.	0.858			
8. YouTube improves my effectiveness in my courses.	0.810			
EE				
9. Learning how to use YouTube for educational purposes is easy for me.	0.846			
10. I find YouTube easy to use.	0.842	0.82	0.61	0.63
11. It is easy to learn something on YouTube.	0.635			
SI				
12. My friends think that I should use YouTube for educational purposes.	0.779			
13. My parents think that I should use YouTube for educational purposes.	0.801	0.89	0.67	0.83
14. My teachers think that I should use YouTube for educational purposes.	0.811			

15. People around me / in my social life think that I should use YouTube for educational purposes.	0.874			
FC				
16. I have the resources necessary to use YouTube for educational purposes.	0.795			
17. I have the skills / knowledge necessary to use YouTube for educational purposes.	0.846			
18. YouTube is compatible with the technology (e.g., my mobile phone, desktop computer, etc.) that I use.	0.877	0.82	0.56	0.58
19. I can get help from others when I have difficulties using YouTube for educational purposes.	0.353			
BI				
20. I think that I will use YouTube for educational purposes.	0.911			
21. I plan to use YouTube for educational purposes.	0.926	0.94	0.84	0.91
22. I intent to use YouTube as a student for the courses that I do not understand / I find difficult to understand.	0.919			

* *Note.* The items were in Turkish, and the language validity for English was not established

Discriminant Validity

Discriminant validity is satisfied when two conceptually different constructs exhibit sufficient difference. There are two indicators for discriminant validity: (1) The Fornell-Larcker criterion, and (2) cross-loadings. To ensure the discriminant validity, Fornell-Larcker criterion suggests that the AVE of each latent variable should be higher than the squared correlations with all other latent variables. Cross-loadings also suggest another way to check the discriminant validity. It is satisfied when all the cross-loadings of individual items under each construct were higher than their factor loadings under other variables. Table 5 demonstrates correlation coefficients and the values of the square root of AVE.

Table 5

Discriminant Validity of the Constructs

Constructs	PE	EE	SI	FC	BI	AU
PE	(0.87)*					
EE	0.288**	(0.78)*				
SI	0.553**	0.210**	(0.82)*			
FC	0.160**	0.69**	0.069**	(0.75)*		
BI	0.784**	0.506**	0.195**	0.195**	(0.92)*	
AU	0.715**	0.417**	0.154**	0.154**	0.680**	(0.93)*

*$p < 0.05$; **$p < 0.01$
Note. Diagonal in parentheses are the values of the square root of AVE; off-diagonal are the values of correlation coefficients.

As it is indicated in Table 5, the square roots of AVE for all the constructs (the values in the parentheses) are greater than the correlation coefficients (the values outside of parentheses); hence, the constructs also satisfy discriminant validity.

Test of the Proposed Model

Hooper, Coughlan, and Mullen (2008) suggested three categories of fit indices to test the measurement model. These indices are: (1) absolute, (2) incremental, and (3) parsimony fit indices. First, absolute fit indices include chi-square ($\chi 2$), relative / normed chi-square ($\chi 2$/df), goodness-of-fit (GFI), adjusted goodness-of-fit (AGFI), root mean square residual (RMSEA), and standardized root mean square residual (SRMR). Second, incremental fit indices include normed-fit index (NFI), non-normed fit index (NNFI), and comparative fit index (CFI). Lastly, parsimony fit indices include parsimony goodness-of-fit index (PGFI) and parsimonious normed fit index (PNFI). Table 6 illustrates the criterion value for each index along with the results obtained in this study. The overall results as illustrated in Table 6 ensured an acceptable fit between the data and proposed model.

Table 6

Model Fit Indices for the Proposed Model

Fit indices	Values	Recommended values
Absolute		
$\chi 2$	422.13	
p value	0.00	≥ .05 (Hair et al., 2006; Hoyle, 1995)
$\chi 2$ / df	2.37	≤ 3 (Kline, 2005)
GFI	.89	≥ .85 (Jöreskog & Sörbom, 1988)
AGFI	.86	≥ .80 (Marsh, Balla, & McDonald, 1988)
RMSEA	.06	≤ .10 (MacCallum, Widaman, Preacher, & Hong, 2001; Bentler & Bonnet, 1980)
SRMR	.08	≤ .10 (Kline, 2005)
Incremental		
NFI	.96	≥ .90 (Bentler &Bonett, 1980)
NNFI	.97	≥.90 (Vidaman & Thompson, 2003; Bentler &Bonett, 1980)
CFI	.98	≥.90 (Vidaman & Thompson, 2003; Bentler, 1990; Bentler &Bonett, 1980)
Parsimony		
PNFI	.82	>.50 (Mualik, James, Van Alstine, Bennett, Lin, & Stilwel, 1989)
PGFI	.69	>.60 (Byrne, 2010)

Test of the Structural Model

To be able to test the proposed hypotheses, standardized path coefficients and their significance were investigated. As it is illustrated in Table 7, BI was predicted by PE and SI, but EE was not a significant predictor of BI. Hence, H1 and H3 was supported, meanwhile H2 was not supported. Furthermore, AU was predicted by BI, but FC was not a significant predictor of AU. In this regard, while H5 was supported, H4 was rejected. PE and SI together explained 91% of the total variance in BI, and BI explained 77% of the variance in AU.

Table 7

Path Coefficients and Their Significance for Hypothesis Testing

Hypothesis number	Proposed hypothesis	Path coefficient	t-value	Study results
H1	PE → BI	.80	13.55	Supported
H2	EE → BI	.05	1.29	Not supported
H3	SI → BI	.11	2.30	Supported
H4	FC → AU	.02	.35	Not supported
H5	BI → AU	.77	14.66	Supported

Discussion and Conclusion

In response to prevalence of YouTube as one of the most common digital resources in educational praxis, this study aimed at investigating high school students' educational use of YouTube. The study underpinned UTAUT as the theoretical framework to identify predictors of acceptance behavior. To this end, performance expectancy (PE), effort expectancy (EE), and social influence (SI) were tested as predictors of behavioral intention (BI), and in turn BI and facilitating conditions (FC) were tested as predictors of actual usage (AU).

Consistent with the prediction of this study, PE was found to be the strongest predictor of BI. In fact, this result is consistent with a plethora of studies that found PE as a dominant predictor of BI (e.g., Chaka & Govender, 2017; Khechine & Lakhal, 2018; Padhi, 2018; Suki & Suki, 2017). For instance, Padhi (2018) investigated faculty perception with respect to open educational resources (OER) by applying UTAUT. The results indicated that PE positively influenced the intentions to use OER. Similarly, Suki and Suki (2017) examined the determinants of students' behavioral intention to use animation and storytelling through UTAUT. The results demonstrated that PE was the strongest predictor of BI to use animations and storytelling within lessons. This implies that participants will be more likely to use YouTube for educational purposes if they perceive learning through this digital resource would improve their academic performance.

In the present study, SI was also found to be significant predictor of BI. In fact, this result is consistent with numerous previous studies (e.g., Abu-Al-Aish & Love, 2013; Isaias, Reis, Coutinho, & Lencastre, 2017; Nicholas-Omoregbe, Azeta, Chiazor, & Omoregbe, 2017; Prasad, Maag, Redestowicz, & Hoe, 2018). For instance, Nicholas-Omoregbe et al. (2017) investigated the factors that have an influence on the adoption of e-learning management system (e-LMS) in higher education. The results demonstrated that SI was one of the strong predictors of BI to adopt e-LMS. Similarly, Prasad et al. (2018) investigated learners' BI to use a blended learning program employed with post-graduate international information technology students. The results showed that SI is a strong predictor on both PE and EE as well as BI. The researchers concluded that SI is one factor to mitigate the barriers to technology adoption. In the context of this study, this result implies that students' educational use of YouTube will more likely to be influenced in case it is accepted by their peers, teachers, and family members, or within their social environment.

This study did not find significant associations between EE and BI, along with FC and AU. EE was measured with three items in accordance with previous studies and comprised participants' perceptions concerning the ease associated with educational use of YouTube. In other words, the educational use of YouTube will be effortless. In fact, the insignificant results concerning EE has been discussed in several studies (e.g., Ali & Arshad, 2018; Doleck, Bazelais, & Lemay, 2017; Isaias et al., 2017; Liu, Chang, Huang, & Chang, 2016). For instance, Isaias et al. (2017) examined the acceptance of an educational forum, which includes empathic and affective characteristics. The results of the study demonstrated that EE was not a significant predictor of BI. Similarly, Doleck et al. (2017) investigated students' computer-based learning environment use by comparing two different models: The Technology Acceptance Model (TAM) and UTAUT. The results demonstrated that the hypothesis developed under the UTAUT model concerning the relationship between EE and BI was not significant. There are two possible factors for the insignificant relationship in the context of this study. First, the participants may perceive YouTube as an easy-to-use platform, and second, the participants may not attribute a degree of difficulty in using YouTube for educational purposes. This generation of students is classified as digital natives who are generally comfortable with using technology. In this regard, their demographic characteristics might also contribute to insignificant association between EE and BI.

Contrary to the prediction of this study, the results showed that FC was not a significant predictor of AU. In fact, the original model of UTAUT posited that FC is a significant determinant of AU. However, there are several studies that did not find significant association between FC and AU (e.g., Khechine & Lakhal, 2018; Yueh, Huang, & Chang, 2015). For instance, Khechine and Lakhal (2018) investigated university students' acceptance of webinar technology and the results of the study demonstrated that FC was not a significant predictor of AU. Yueh et al. (2015) examined factors that influence students' adaptation and continued use of a Wiki system and the results of the study demonstrated that FC was not a significant predictor of AU. There might be three plausible explanations of the insignificant association between FC and AU in the context of this study. This study conceptualized FC as participants' perceptions on whether they have access to resources and support to use YouTube for educational purposes. First, the majority of the participants reported that they have mobile phones and access to the Internet. Hence, they have the required hardware and software to access YouTube as one of the required resources. Furthermore, these participants are categorized as digital natives that could easily navigate on a digital world without any assistance from others. In this regard, the lack of a specific person or group for assistance with difficulties on the use of YouTube for educational purposes might not contribute to explaining the extent of variance in AU. Third, the usability of YouTube might not create system difficulties and as a result it may not be a barrier to AU.

This study also tested the hypothesis that BI is a significant predictor of AU as originally validated in UTAUT model. In fact, there are several studies found that BI is a significant determinant of AU (e.g., Liu et al., 2016; Doleck et al., 2017). For instance, Liu et al. (2016) investigated students' BI to use social networking services (SNS) and found that BI was a significant predictor of AU. Similarly, Doleck et al. (2017) investigated students' computer-based learning environment use and they found a significant positive relationship between BI and AU. Consistent with the prediction of this study, the structural equation analysis demonstrated that BI was a significant predictor of the AU of YouTube for educational purposes. In the context of this study, this implies that the stronger the intention, the more likely that participants will use YouTube for educational purposes.

Limitations and Future Research

This study has numerous limitations concerning several stages, including but not limited to, the theoretical framework of the study, the data collection, and the sampling method, which can potentially create an avenue for future studies. First, this study underpinned the core constructs as postulated and tested by UTAUT. Hence, future studies can further synthesize the model by including various constructs from other technology acceptance theories that will possibly increase the predictive power. For instance, media richness might be used to extend the potential of YouTube in educational settings as it assumes that users will be more likely to adopt rich media, including immediate feedback or language variety. Second, the data of the study were collected by means of a self-report measure without any triangulation of the data sources. Thus, future research needs to include different sources of data in order to gain deeper insights. Third, this study underpinned the convenience sampling method, which has a potential bias as the participants were within the same age level and demographics. Thus, the results might not be a representative of other age levels and may not be generalizable. In this regard, future studies should try to include participants from different age levels and cultural backgrounds. Finally, teachers are one of the most important role models for students studying at the high school level and they might play a significant role in the adoption of YouTube as an educational resource. Considering the significant determinant of SI in this study, teachers have the potential of improving students' perception toward the use of YouTube for their educational needs. From this perspective, there is a need to investigate teachers' perceptions toward educational use of YouTube.

References

Abu-Al-Aish, A., & Love, S. (2013). Factors influencing students' acceptance of m-learning: An investigation in higher education. *The International Review of Research in Open and Distance Learning, 14*(5), 82-107. DOI: 10.19173/irrodl.v14i5.1631

Adhikari, J., Sharma, P., Arjyal, L., & Uprety, D. (2016). YouTube as a source of information on cervical cancer. *North American Journal of Medical Sciences, 16*(8), 183-186. DOI: 10.4103/1947-2714.179940

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. DOI: 10.1016/0749-5978(91)90020-T

Ali, R. A., & Arshad, M. R. M. (2018). Empirical analysis on factors impacting on intention to use m-learning in basic education in Egypt. *International Review of Research in Open and Distributed Learning, 19*(2), 253-270. DOI: 10.19173/irrodl.v19i2.3510.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238–246. DOI: 10.1037/0033-2909.107.2.238

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness-of-fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588–606. DOI: 10.1037/0033-2909.88.3.588

Bonk, C. J. (2008, March). *YouTube anchors and enders: The use of shared online video content as a macrocontext for learning*. Paper presented at the American Educational Research Association (AERA) 2008 Annual Meeting, New York, NY.

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming (2nd edition)*. MA: Routledge.

Chaka, J. G., & Govender, I. (2017). Students' perceptions and readiness towards mobile learning in colleges of education: A Nigerian perspective. *South African Journal of Education, 37*(1), 1-12. DOI: 10.15700/saje.v37n1a1282

Çokluk, Ö., Şekercioğlu, G., & ve Büyüköztürk, Ş. (2016). *Sosyal bilimler için çok değişkenli istatistik SPSS ve LISREL Uygulamaları* [Multivariate statistics for social sciences: SPSS and Lisrel applications]. Ankara: Pegem Akademi Yayıncılık.

Doleck, T., Bazelais, P., & Lemay, D. J. (2017). Examining CEGEP students' acceptance of computer-based learning environments: A test of two models. *Education and Information Technologies, 22*, 2523-2543. DOI: 10.1007/s10639-016-9559-9

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the unified theory of acceptance and use of technology 2 (UTAUT2). *Educational Technology Research and Development*, *65*(3), 743-763. DOI: 10.1007/s11423-016-9508-8

Erstad, O. (2012). The learning lives of digital youth – beyond the formal and informal. *Oxford Review of Education, 38*(1), 25-43. DOI: 10.1080/03054985.2011.577940

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. DOI: 10.2307/3151312

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis.* New Jersey: Pearson Education Inc.

Hao, S., Dennen, V. P., & Mei, L. (2017). Influential factors for mobile learning acceptance among Chinese users. *Educational Technology Research and Development, 65*(1), 101-123. DOI: 10.1007/s11423-016-9465-2

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods, 6*(1), 53-60.

Hoyle, R. H. (1995). *Structural equation modeling: concepts, issues, and application*. London: Sage.

Im, I., Hong, S., & Kang, M. S. (2011). An international comparison of technology adoption: Testing the UTAUT model. *Information & Management, 48*(1), 1-8. DOI: 10.1016/j.im.2010.09.001

Isaias, P., Reis, F., Coutinho, C., & Lencastre, J. A. (2017). Empathic technologies for distance/mobile learning: An empirical research based on the unified theory of acceptance and use of technology (UTAUT). *Interactive Technology and Smart Education, 14*(2), 159-180. DOI: 10.1108/ITSE-02-2017-0014

Jöreskog, K. G., & Sörbom D. (1988). *LISREL 7: A guide to the program and applications*. Chicago, IL: SPSS Inc.

Jung, I., & Lee, Y. (2015). YouTube acceptance by university educators and students: A cross-cultural perspective. *Innovations in Education and Teaching International, 52*(3), 243-253. DOI: 10.1080/14703297.2013.805986

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. DOI: 10.1007/bf02291575

Khechine, H., & Lakhal, S. (2018). Technology as a double-edged sword: From behavior prediction with UTAUT to students' outcomes considering personal characteristics. *Journal of Information Technology Education, 17,* 63-102. DOI: 10.28945/4022

Kline, R.B. (2005). *Principles and practice of structural equation modeling (2nd ed.).* New York, NY: Guilford Press.

Lin, C. C., & Polaniecki, S. (2009). From media consumption to media production: Applications of YouTube™ in an eighth-grade video documentary project. *Journal of Visual Literacy*, *28*(1), 92-107. DOI: 10.1080/23796529.2009.11674661

Lin, S., Zimmer, J. C., & Lee, V. (2013). Podcasting acceptance on campus: The differing perspectives of teachers and students. *Computers & Education, 68,* 416-428. DOI: 10.1016/j.compedu.2013.06.003

Liu, L. -W., Chang, C. -M, Huang, H. -C., & Chang, Y. -L. A. (2016). Verification of social network site use behavior of the university physical education students. *Eurasia Journal of Mathematics, Science & Technology Education, 12*(4), 793-805. DOI: 10.12973/eurasia.2016.1232a

MacCallum, R. C., Widaman, K. F., Preacher, K., & Hong, S. (2001). Sample size in factor analysis: The role of model error. *Multivariate Behavioral Research, 36,* 611–637. DOI: 10.1207/S15327906MBR3604_06

Madden, M. (2009, July 29). The audience for online video-sharing sites shoots up (Blog post). Retrieved from http://www.pewinternet.org/2009/07/29/the-audience-for-online-video-sharing-sites-shoots-up/

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indexes in confirmatory factor analysis: The effect of sample size. *Psychological Bulletin, 103*, 391–410. DOI: 10.1037/0033-2909.103.3.391

Mualik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lin, S., & Stilwel, C. D. (1989). Evaluation of goodness of fit Indices for structural equation models. *Psychological Bulletin, 105*(3), 430–445. DOI: 10.1037/0033-2909.105.3.430

Ngampornchai, A., & Adams, J. (2016). Students' acceptance and readiness for E-learning in Northeastern Thailand. *International Journal of Educational Technology in Higher Education, 13*(34), 1-13. DOI: 10.1186/s41239-016-0034-x

Nicholas-Omoregbe, O. S., Azeta, A. A., Chiazor, I. A., & Omoregbe, N. (2017). Predicting the adoption of e-learning management system: A case of selected private universities in Nigeria. *Turkish Online Journal of Distance Education*, *18*(2), 106-121. DOI: 10.17718/tojde.306563

Nistor, N., Göğüş, A., & Lerche, T. (2013). Educational technology acceptance across national and professional cultures: A European study. *Educational Technology Research and Development, 61*(4), 733-749. DOI: 10.1007/s11423-013-9292-7

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity, 41*(5), 673-690. DOI: 10.1007/s11135-006-9018-6

Padhi, N. (2018). Acceptance and usability of OER in Indian higher education: An investigation using UTAUT model. *Open Praxis, 10*(1), 55-65. DOI: 10.5944/openpraxis.10.1.623

Podsakoff P. M., MacKenzie, S. B., Lee, J. –Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. DOI: 10.1037/0021-9010.88.5.879

Prasad, P.W.C., Maag, A., Redestowicz, M., & Hoe, L. S. (2018). Unfamiliar technology: Reaction of international students to blended learning. *Computers & Education, 122,* 92-103. DOI: 10.1016/j.compedu.2018.03.016

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research, 99*(6), 323–337. DOI: 10.3200/JOER.99.6.323-338

Suki, N. M., & Suki, N. M. (2017). Determining students' behavioral intention to use animation and storytelling applying the UTAUT model: The moderating roles of gender and experience level. *The International Journal of Management Education, 15,* 528-538. DOI: 10.1016/j.ijme.2017.10.002

Šumak, B., & Šorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre-and post-adopters. *Computers in Human Behavior, 64*, 602-620. DOI: 10.1016/j.chb.2016.07.037

Teo, T., & Noyes, J. (2014). Explaining the intention to use technology among pre-service teachers: A multi-group analysis of the unified theory of acceptance and use of technology. *Interactive Learning Environments, 22*(1), 51-66. DOI: 10.1080/10494820.2011.641674

Terlemez, M. S. (2016). YouTube channels as support materials in distance learning. *Journal of Educational and Instructional Studies, 6*(4), 77-88.

Ünlüsoy, A., de Haan, M., Leander, K., & Volker, B. (2013). Learning potential in youth's online networks: A multilevel approach. *Computers and Education, 68,* 522-533. DOI: 10.1016/j.compedu.2013.06.007

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. DOI: 10.2307/30036540

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: US vs. China. *Journal of Global Information Technology Management, 13*(1), 5-27. DOI: 1097198X.2010.10856507

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. DOI: 10.2307/41410412

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems, 17*(5), 328-376. DOI: 10.17705/1jais.00428

Vidaman, K. F., & Thompson, J. S. (2003). On specifying the null model for incremental fit indices in structural equation modeling. *Psychological Methods, 8*(1), 16–37. DOI: 10.1037/1082-989X.8.1.16

Wong, G. K. W. (2016). The behavioral intentions of Hong Kong primary teachers in adopting educational technology. *Educational Technology Research and Development, 64*(2), 313-338. DOI: 10.1007/s11423-016-9426-9

Wong, K. T., Teo, T., & Goh, P. S. C. (2015). Understanding the intention to use interactive whiteboards: Model development and testing. *Interactive Learning Environments, 23*(6), 731-747. DOI: 10.1080/10494820.2013.806932

Yueh, H. –P., Huang, J. –Y., & Chang, C. (2015). Exploring factors affecting students continued Wiki use for individual and collaborative learning: An extended UTAUT perspective. *Australasian Journal of Educational Technology, 31*(1), 16-31. DOI: 10.14742/ajet.170