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Social Network Sites Impact on Learning: Extending the TAM 3 Model to Assess Academic Performance in Higher Education

S. A. Barabadi[1], A. Shams[2*], and N. Wise[3]

ABSTRACT

Examining the capabilities of social network sites in teaching and learning can be useful in higher education and can help improve students' performance. This study investigated the factors affecting acceptance and educational use of social network sites and the effect of this use on academic performance by using the Technology Acceptance Model3. Four hundred agricultural students participated in the study survey, and data were analyzed through Structural Equation Modelling. Results show that the subjective norm, image, job relevance, and output quality were the predictors of perceived usefulness. Self-efficacy, anxiety, playfulness, and perceived enjoyment were also predictors of perceived ease of use. Findings suggest that perceived usefulness and perceived ease of use had significant effects on behavioural intention to use, and this last variable had a significant effect on actual use. Educational use of social network sites also had a strong positive impact on academic performance.

Keywords: Behavioural intention, Structural Equation Modelling, Technology Acceptance Model 3.

INTRODUCTION

With technology changing how we teach today, it is important to revise strategies that focus on contemporary ways of transferring knowledge, which is especially essential in the agriculture education systems (Deegan *et al*., 2015). Research has shown that student engagement with different technologies plays a vital role in their future achievements (Dahlstrom, 2012). Therefore, students see technology as indispensable and integral to their educational success (Galanek *et al*., 2018). Nowadays, one of the most popular types of technology that have great potential to enhance the teaching and learning experience is Social Network Sites (SNS) (Hamid *et al*., 2015). It is often thought that the use of SNSs in agricultural education is not possible due to the specific type of courses students take in these disciplines, but Kipkurgat *et al*. (2016) believe that, among the new educational technologies, SNSs are essential in the agricultural education system as a means of conveying educational messages. Many studies show that a remarkable percent of agricultural students are using SNS every day (Kabir *et al*., 2016; Murphrey *et al*., 2012).

Despite the widespread use of SNSs among agricultural students and professors, and the capabilities that this technology has for teaching and learning in agricultural higher education, there is need to incorporate these technologies into university curricula (Owusu *et al*., 2019). However, students and

[1] Department of Agricultural Extension and Education, Faculty of Agriculture and Natural Resources, Saravan Higher Education Complex, Saravan, Islamic Republic Iran.
[2] Department of Agricultural Extension, Communication and Rural Development, Faculty of Agriculture, University of Zanjan, Zanjan, Islamic Republic Iran.
[3] School of Community Resources and Development, Arizona State University, Arizona, U.S.A.
*Corresponding author; e-mail: Shams@znu.ac.ir

professors still express doubt regarding the use of SNSs in teaching and learning. Kabir *et al*. (2016) showed that most of agricultural students use SNSs as recreational media to connect with friends and family. Cramer (2013), Murphrey *et al*. (2012), and Ogaji *et al*. (2017) also found similar findings. However, contrary to this point, students believe that SNSs can be a useful tool in agricultural higher education classes (Kabir *et al*., 2016).

This study investigates factors that lead to the adoption and use of SNSs in teaching and learning activities. This paper assesses the impact of SNS on the academic performance of students. This represents a gap in the literature since studies too often explore engagement, but with limited focus on performance. Performance in education is an essential topic, yet insufficiently investigated (Doleck and Lajoie, 2018). SNSs have been common in Iran for decades, but the use of SNSs in the agricultural higher education system requires attention. Today, one of the criticisms of agricultural higher education in Iran is that most of the teaching time at the university is devoted to theoretical topics and less to skill training. This allocation of more time to theoretical topics, among other reasons, has led to low skills of agricultural graduates. Providing a large portion of theoretical topics through SNS can give agricultural professors more opportunity to devote their time to practical training. On the other hand, most farmers in rural Iran have only recently gained access to internet infrastructure, and the Agricultural Research, Education and Extension Organization of Iran have launched a website (https://agrilib.areeo.ac.ir) to educate farmers virtually. Based on recent developments, this work offers both a conceptual gap to understand performance and contextualize findings for broader higher education settings. This paper also provides a specific focus for Iran going forward.

Today, SNSs have gone beyond their primary goals of social interaction, communication, cognition, and advertising, and now have a new purpose that includes education (Doğan *et al*., 2018). SNSs can contribute to the classroom learning activities to facilitate learning. This creates a flexible e-learning environment open to learners, especially in higher education (Luo *et al*., 2019). As e-learning is now becoming a widespread approach in higher education institutions (Persico *et al*., 2014), the use of SNS for education and learning is also increasing among faculty and students. Millions of users, including students, have been attracted to SNS around the world, and it is believed that these networks can be used to complement traditional and online classroom activities (Alizadeh, 2018).

Research praises social networking tools for their ability to attract, stimulate, and encourage students in meaningful communication activities, content exchange, and collaboration, but we still need to understand how this impacts performance (Zaidieh, 2012). An important question concerning the use of SNS by students is the effects it has on academic performance (Doleck *et al*., 2018). While researchers have indicated negative relationships between using SNSs and academic performance (Giunchiglia *et al*., 2018; Liu *et al*., 2017), it is still important to differentiate between using SNS for educational and non-educational purposes. In a study on Serbian students, Lambić (2016) showed that the frequency of using Facebook for educational purposes has a significant impact on the academic performance of students. Ainin *et al*. (2015) confirmed this result in Malaysian students. In another study in Malaysian higher education, Al-Rahmi and his colleagues (2014) showed that the academic performance of students would improve by using social media through collaborative learning.

For technologies to be developed beneficially, they must be accepted and used by individuals (Venkatesh *et al*., 2003). Many researchers have studied factors affecting the acceptance and use of technologies in education and learning. For instance, Galanek *et al*. (2018) showed that students' demographic features and their technology experience are critical factors, this includes the type of technology most useful for helping them succeed. Owusu *et al*. (2019) also found that perceived usefulness, perceived ease of use, the existence of facilitating conditions, and the purposes of SNSs are the crucial factors for motivating students in adapting SNSs for education and learning. Nevertheless, the important thing is the lack of a complete and integrated model in such studies that includes all the influential factors.

In higher education, there are many theories and models used to understand and explain factors affecting the acceptance and use of innovation (Saini and Abraham, 2019). The study in this area has led to the emergence of several theoretical models rooted in information systems, psychology, and social sciences, and typically explain more than 40% of the variance in the individuals' intention to use technology (Venkatesh *et al*., 2003). One of the most popular models in this area is the Technology Acceptance Model (TAM). TAM and its extensions have been the most widely used to investigate the behaviour of technology acceptance (including SNS) in different fields (Alshurideh *et al*., 2019; Leong *et al*., 2018; Nikolopoulos and Likothanassis, 2018; Sánchez-Prieto *et al*., 2017).

The last modification of TAM is called TAM 3, established by Venkatesh and Bala (2008). TAM 3 has two main variables of TAM, including Perceived Usefulness (PU) and Perceived Ease of Use (PEU), and various variables that influence these two variables. This model is a breakthrough in technology adoption. Undoubtedly, TAM 3 theory has made significant theoretical contributions by recognizing the determinants of PU and PEU (Faqih *et al*., 2015), and offers a complete nomological network of individuals' acceptance and use of information technology determinants (Momani *et al*., 2018). This model is more comprehensive in terms of understanding new information technologies by individuals, compared with previous models (Venkatesh and Bala, 2008). The TAM 3 is applied to identify the factors affecting acceptance and usage of various technologies in learning and education by students (e.g., Al-gahtani, 2016). However, few studies are assessing the acceptance of SNSs in teaching and learning among students using the TAM 3 model.

MATERIALS AND METHODS

Research Model and Hypotheses

TAM 3 presents the most complete TAM version (Yousafzai, 2012) and provides a complete set of determinants for understanding individuals' acceptance and use of information technology (Venkatesh and Bala, 2008). As a research model for this study, some variables in the original TAM 3 model were removed, with insight included in exploring academic performance (Figure 1). Table 1 presents the definitions of the constructs in the research model.

This study had 16 hypotheses, except for the relationship between "computer anxiety" and "perceived ease of use", which is negative, all the relationships were assumed to be positive. Table 2 shows these hypotheses and their related evidence in previous researches.

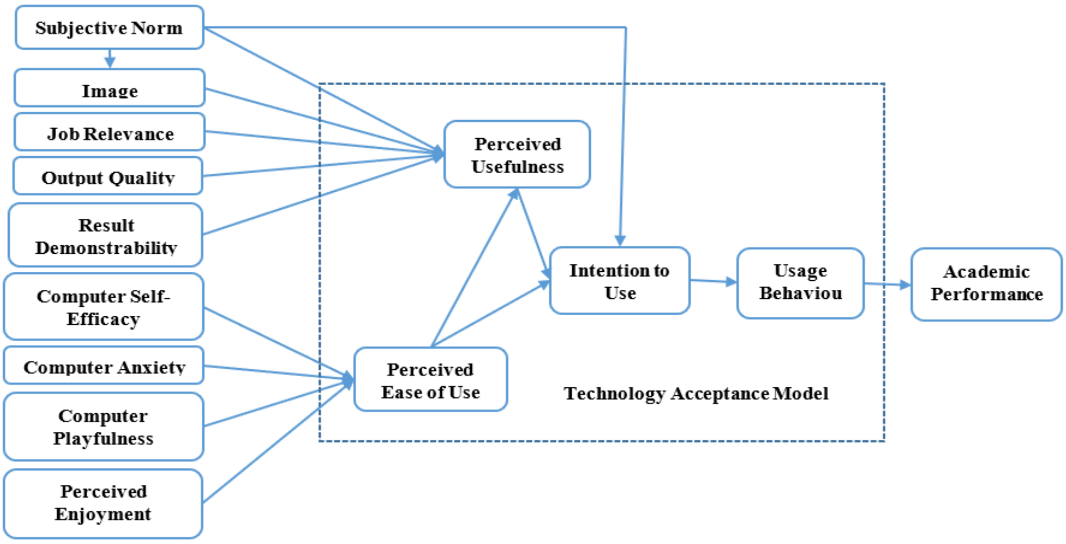

Figure 1. Research model and conceptual framework displaying factors through the TAM 3 model that influence academic performance.

Table 1. Definition of constructs of factors influencing academic performance through the TAM 3 model.

Construct	Definition
Subjective Norm (SN)	Person's perception that most people who are important to him think he should or should not perform the behavior in question (Fishbein and Ajzen, 1975).
Image (IMG)	The degree to which the use of an innovation is perceived to enhance one's image or status in one's social system (Moore and Benbasat, 1991).
Job Relevance (REL)	The degree to which a person believes that a system (such as new technology) applies to his/her job (Venkatesh and Davis, 2000).
Output Quality (OUT)	The degree to which a person believes that a system performs his/her job tasks well (Venkatesh and Davis, 2000).
Result Demonstrability (RES)	The extent to which a person believes that the results of using a system are tangible, observable, and communicable (Venkatesh and Bala, 2008).
Computer Self-Efficacy (SE)	A person's belief in her/his ability to perform a specific task/job using a computer (Venkatesh, 2000).
Computer Anxiety (ANX)	The fear or apprehension that people feel when they use a computer or consider the possibility of using it (Simonson *et al.*, 1987).
Computer Playfulness (PL)	An intrinsic motivation for using any new technology (Venkatesh and Bala, 2008).
Perceived Enjoyment (ENJ)	Apart from any performance consequences that may be foreseen, the activity of using the computer itself is perceived to be enjoyable (Bagozzi *et al.*, 1992).
Perceived Usefulness (PU)	The degree to which a person thinks that utilizing a particular system would enhance his performance (Davis, 1989).
Perceived Ease of Use (PEU)	"The degree to which a person believes that using a particular system would be free of effort" (Venkatesh and Davis, 2000).
Behavior Intention (BI)	A sign of a person's readiness to perform a behavior (Fishbein and Ajzen, 2011).
Use Behavior (USE)	The actual usage of SNSs by students for education and learning.
Academic Performance (AP)	Students' reporting of past semester CGPA/GPA and their expected GPA for the current semester (Masrom and Usat, 2015).

Research Design and Data Collection

This is an applied study in terms of purpose, and a survey study in terms of data collection. This study was conducted in early 2019 and before the COVID-19 pandemic became widespread in Iran. The data collection tool was a structured questionnaire consisting of two parts. The first part contained information about students' demographic characteristics and the second part included the factors affecting the educational use of SNS. To measure TAM 3 variables, the researchers used the specific questions derived from literature, particularly from Venkatesh and Bala (2008). The items were developed according to the context of SNS and education. This part of the questionnaire

Table 2. Research hypotheses regarding constructs relationship and previous research evidence.

Hypothesis	Relationship	Influence	Researchers	Supported	Not supported	Hypothesis	Relationship	Influence	Researchers	Supported	Not supported
H1	SN → PU	+	Al-Gahtani (2016)	*		H9	PL → PEU	+	Al-Gahtani (2016)	*	
			Müller (2013)	*					Müller (2013)	*	
H2	SN → IMG	+	Al-gahtani (2016)	*					Jeffrey (2015)		*
			Müller (2013)	*					Binobaid (2017)		*
H3	IMG → PU	+	Al-gahtani (2016)	*		H10	ENJ → PEU	+	Al-Gahtani (2016)	*	
			Venkatesh and Davis (2000)	*					Venkatesh and Bala (2008)	*	
			Jeffrey (2015)		*				Binobaid (2017)	*	
			Binobaid (2017)		*				Jeffrey (2015)	*	
H4	REL → PU	+	Al-Gahtani (2016)	*		H11	PEU → PU	+	Dumpit and Fernandez (2017)	*	
			Jeffrey (2015)	*					Venkatesh and Bala (2008)	*	
			Binobaid (2017)		*	H12	SN → BI	+	Dumpit and Fernandez (2017)	*	
H5	OUT → PU	+	Müller (2013)	*					Al-gahtani (2016)	*	
			Jeffrey (2015)	*					Venkatesh and Davis (2000)	*	
			Binobaid (2017)	*		H13	PU → BI	+	Owusu *et al.* (2019)	*	
H6	RES → PU	+	Venkatesh and Bala (2008)	*					Dumpit and Fernandez (2017)	*	
			Binobaid (2017)	*					Zaki and Khan (2016)	*	
			Jeffrey (2015)	*					Moorthy *et al.* (2019)	*	
			Al-gahtani (2016)		*	H14	PEU → BI	+	Moorthy *et al.* (2019)	*	
H7	SE → PEU	+	Venkatesh and Bala (2008)	*					Dumpit and Fernandez (2017)	*	
			Al-Gahtani (2016)	*					Owusu *et al.* (2019)	*	
			Jeffrey (2015)		*				Zaki and Khan (2016)	*	
			Binobaid (2017)		*	H15	BI → USE	+	Dumpit and Fernandez (2017)	*	
H8	ANX → PEU	-	Al-Gahtani (2016)	*					Müller (2013)		*
			Binobaid (2017)	*		H16	USE → AP		Lambić (2016)	*	
			Jeffrey (2015)		*				Moorthy *et al.* (2019)	*	
			Müller (2013)		*				Manca and Ranieri (2013)	*	

contained 42 items on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

This study made use of three data collection methods: Sending online questionnaire links via SNS, sending questionnaires via e-mail, and asking students to complete printed questionnaires during class time. Participants were reassured about voluntary participation, anonymous, and confidential information; and the extracted data being used just for the research.

Participants

According to Hair *et al*. (2014), more measured or indicator variables require larger samples. Therefore, model complexity leads to the need for larger samples. Since this research has a complex model with many variables, a sample of 400 students studying agriculture at eight public universities in Iran participated, using a randomized multistage sampling method involving two steps. In the first step, randomized cluster sampling was used based on universities' classification by the Ministry of Science, Research and Technology of Iran; two universities from each level were selected. This classification is based on performance level and includes 4 levels: international, national, regional, and local. In choosing universities, in addition to having a faculty of agriculture, their geographical distribution was also considered. In the second step, in each agricultural college, data collected involved a randomized sampling method.

Since the sample size was estimated to be 400, 500 students were selected to ensure the return of the appropriate number of questionnaires. Of these, 423 questionnaires were completed. After removing the incomplete and unacceptable questionnaires, 400 questionnaires were evaluated.

According to Table 3, most of the respondents were women and were between 21 and 30 years old. Most of them were related to Agricultural Sciences and Natural Resources University of Khuzestan. Also, most of the students were studying in bachelor's degree and their GPA was between 15.01 and 18. According to the results, most of the respondents have used social network sites in education between 1.01 and 3 hours a day.

Table 3. Frequency distribution of students participating in research according to demographic characteristics.

Demographic profile	Frequency	Percentage (%)	Demographic profile	Frequency	Percentage (%)
Gender			Level of education		
Female	230	57.5	Associate	7	1.8
Male	170	42.5	Bachelor	196	49
Age			Masters	112	28
Lowest through 20	71	17.8	Ph.D.	84	21
21 through 30	264	66	No response	1	0.3
31 through 40	52	13	GPA		
41 through highest	13	3.3	10 through 12	27	6.8
University			12.01 through 15	70	17.5
Bu-Ali Sina University	44	11	15.01 through 18	243	60.8
Higher Educational Complex of Saravan	28	7	18.01 through 20	60	15
University of Jiroft	52	13	Total use of SNSs in education (hours in a day)		
University of Tabriz	64	16	Lowest through 1	162	40.5
Sari Agricultural Sciences and Natural Resources University	48	12	1.01 through 3	172	43
Shiraz University	52	13	3.01 through 5	49	12.3
Agricultural Sciences and Natural Resources University of Khuzestan	76	19	5.01 through 7	10	2.5
University of Zanjan	36	9	7 through highest	7	1.8

Data Analysis

Structural Equation Modelling (SEM) was used to analyze data and examine the research hypotheses. Since this study sought to investigate the factors affecting students' use of SNSs in learning processes and our model had several constructs, PLS-SEM was the most appropriate data analysis method for this study (Hair *et al*., 2011). Therefore, Smart PLS 2.0 was used for data analysis.

RESULTS

Measurement Model

The aim of testing the measurement model is to specify how the latent variables are measured in terms of the observed variables, and how these are used to describe the measurement properties of the observed variables (Chou, 2006).

According to the results (Table 4), all factor loadings, except one item (PEU2), were above 0.7 (Hair *et al*., 2011). The results also show a Cronbach's Alpha range from 0.719 to 0.902, all exceeding the 0.70 threshold. The minimum Composite Reliability (CR) of these variables is 0.835, so, they meet the recommended threshold value of 0.70 (Nunnally, 1978). Convergent validity of constructs was tested by Average Variance Extracted (AVE). Results showed that all AVE values were above 0.50, thus deemed acceptable (Henseler *et al*., 2009).

To accept the discriminant validity, Fornell and Larcker (1981) method was used (Table 5). Results showed that the square root of the AVE of each latent variable (bolded values) was greater than the correlations between that variable and other variables. The HTMT ratio was also evaluated to ensure accurate measurement of the model. These values are shown in parentheses and were all less than 0.9.

Overall, the result of the measurement model shows that item reliability, convergent validity, and discriminant validity of constructs are all satisfactory.

Table 4. Values of Factor Loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted of items and Constructs.

Construct	Items	FL	α	CR	AVE	Construct	Items	FL	α	CR	AVE
Subjective Norm	SN1	0.842	0.749	0.857	0.667	Computer Self Efficacy	SE1	0.855	0.719	0.835	0.629
	SN2	0.850					SE2	0.780			
	SN3	0.755					SE3	0.739			
Image	IMG1	0.818	0.729	0.847	0.648	Computer Anxiety	ANX1	0.853	0.838	0.902	0.755
	IMG2	0.794					ANX2	0.884			
	IMG3	0.804					ANX3	0.871			
Job Relevance	REL1	0.858	0.817	0.889	0.728	Computer Playfulness	PL1	0.804	0.734	0.850	0.653
	REL2	0.872					PL2	0.817			
	REL3	0.828					PL3	0.804			
Output Quality	OUT1	0.799	0.851	0.911	0.774	Perceived Enjoyment	ENJ1	0.886	0.837	0.902	0.754
	OUT2	0.912					ENJ2	0.859			
	OUT3	0.922					ENJ3	0.860			
Result Demonstrability	RES1	0.958	0.902	0.940	0.841	Perceived Ease of Use	PEU1	0.778	0.724	0.844	0.644
	RES2	0.828					PEU3	0.809			
	RES3	0.958					PEU4	0.820			
Perceived Usefulness	PU1	0.843	0.879	0.917	0.734	Behavioral Intention	BI1	0.837	0.844	0.896	0.682
	PU2	0.844					BI2	0.871			
	PU3	0.888					BI3	0.795			
	PU4	0.854					BI4	0.799			

Note: PEU2 is deleted because of low factor loading.

Table 5. Discriminant Validity by using of Fornell and Larcker method.

Var	ANX	BI	ENJ	IMG	OUT	PEU	PL	PU	REL	RES	SE	SN
ANX	**0.869**											
BI	-0.338 (0.402)	**0.826**										
ENJ	-0.607 (0.724)	0.608 (0.724)	**0.868**									
IMG	-0.287 (0.366)	0.564 (0.717)	0.445 (0.567)	**0.804**								
OUT	-0.210 (0.248)	0.747 (0.837)	0.458 (0.542)	0.590 (0.747)	**0.880**							
PEU	-0.647 (0.832)	0.643 (0.823)	0.851 (0.844)	0.510 (0.701)	0.502 (0.639)	**0.802**						
PL	-0.575 (0.733)	0.606 (0.768)	0.742 (0.839)	0.456 (0.622)	0.441 (0.558)	0.786 (0.847)	**0.808**					
PU	-0.389 (0.454)	0.799 (0.828)	0.610 (0.711)	0.718 (0.846)	0.766 (0.842)	0.665 (0.833)	0.581 (0.722)	**0.857**				
REL	-0.344 (0.410)	0.712 (0.846)	0.543 (0.642)	0.634 (0.811)	0.629 (0.744)	0.574 (0.733)	0.510 (0.654)	0.795 (0.812)	**0.853**			
RES	-0.201 (0.227)	0.453 (0.519)	0.345 (0.397)	0.401 (0.494)	0.387 (0.440)	0.355 (0.438)	0.316 (0.388)	0.474 (0.530)	0.496 (0.581)	**0.917**		
SE	-0.478 (0.577)	0.603 (0.769)	0.668 (0.816)	0.485 (0.661)	0.458 (0.573)	0.775 (0.849)	0.658 (0.847)	0.619 (0.777)	0.517 (0.667)	0.320 (0.411)	**0.793**	
SN	-0.277 (0.350)	0.734 (0.816)	0.500 (0.631)	0.625 (0.844)	0.669 (0.838)	0.543 (0.738)	0.515 (0.695)	0.804 (0.844)	0.692 (0.812)	0.450 (0.547)	0.545 (0.756)	**0.817**

Structural Model

For assessing the structural model, initially tests the significance of the paths. According to the results of Table 6 and Figure 2, all t-values are above 1.96, so, all relationships are statistically significant, except for the RES → PU relationship.

Table 6. Values of t-test and making decisions about research hypotheses.

Hypothesis	Relation	Std beta	Std error	t-Value	Decision
H1	SN → PU	0.274	0.037	7.873	Supported
H2	SN → IMG	0.625	0.042	14.807	Supported
H3	IMG → PU	0.152	0.030	4.989	Supported
H4	REL → PU	0.255	0.032	7.892	Supported
H5	OUT → PU	0.246	0.035	7.075	Supported
H6	RES → PU	0.010	0.028	0.531	Not Supported
H7	SE → PEU	0.297	0.029	10.180	Supported
H8	ANX → PEU	-0.133	0.025	5.307	Supported
H9	PL → PEU	0.200	0.037	5.421	Supported
H10	ENJ → PEU	0.423	0.033	12.743	Supported
H11	PEU → PU	0.165	0.033	4.954	Supported
H12	SN → BI	0.254	0.046	4.410	Supported
H13	PU → BI	0.464	0.066	7.009	Supported
H14	PEU → BI	0.197	0.038	5.184	Supported
H15	BI → USE	0.272	0.042	6.544	Supported
H16	USE → AP	0.585	0.025	22.978	Supported

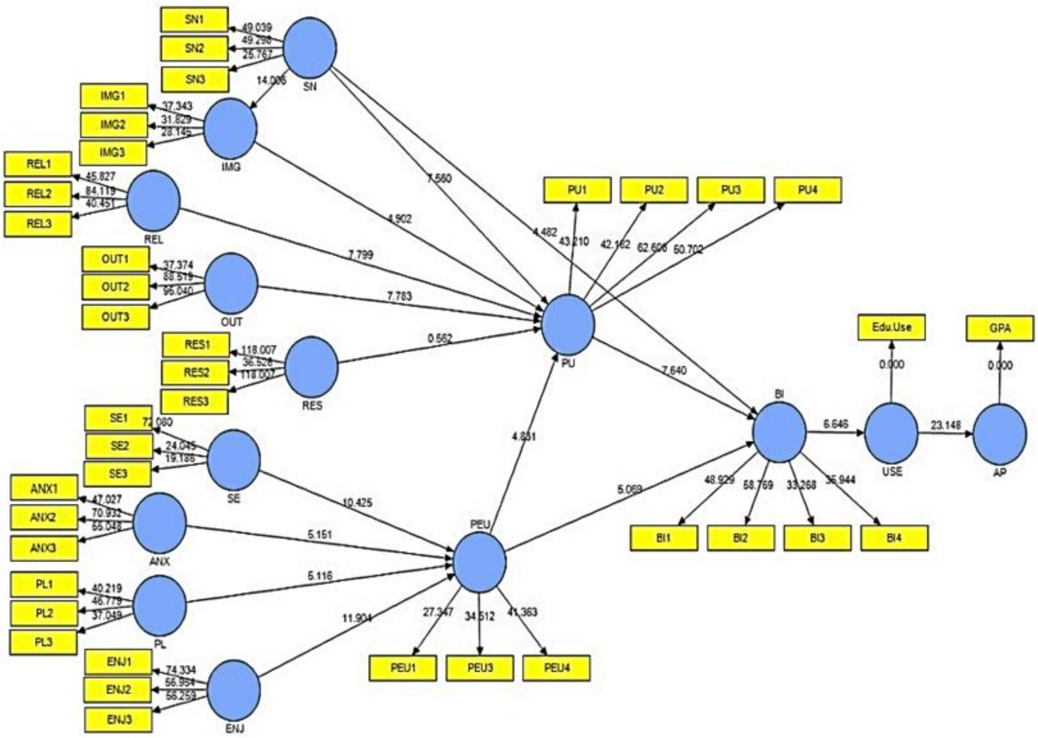

Figure 2: Results of the bootstrapping technique.

The predictive power of the structural model is assessed by the coefficients of determination (R^2) values of the endogenous constructs (Chin, 2010). According to Henseler *et al*. (2009), R^2 values of 0.67, 0.33, and 0.19 can be considered strong, moderate, and weak, respectively. The results show coefficients of determination of PU, PEU and BI are 'strong', IMG and AP are 'moderate', and USE is 'week' (Table 7).

For assessment of the capability to predict the model, researchers use Stone-Geisser's Q^2. Hair *et al*. (2011) believe that the positive values of Q^2 indicate the predictive relevance of a model, which indicates that this model has predictive relevance (Table 7).

Table 7: The predictive power and the capability to predict the model.

Variables	R^2	Result	SSO	SSE	Q^2
Image (IMG)	0.391	Moderate	1200.0000	898.860189	0.250950
Perceived Usefulness (PU)	0.835	Strong	1600.0000	626.590641	0.608381
Perceived Ease of Use (PEU)	0.834	Strong	1200.0000	558.485919	0.534595
Behavioral Intention (BI)	0.683	Strong	1600.0000	868.189900	0.457381
Use (USE)	0.074	Weak	400.0000	370.830477	0.072924
Academic Performance (AP)	0.343	Moderate	-	-	-

DISCUSSION

This study investigated factors affecting the use of SNS in the educational domain by agricultural students. According to the results, among the determinants of the Perceived Usefulness, SN, IMG, REL, and OUT are the significant constructs. It seems natural that the opinion of others makes a person think that by accepting and using SNS he/she can improve his/her educational performance. Also, if students find that educational use of SNS improves their position among their classmates and teachers, then, it can also improve their academic performance. Regarding the relationship of job relevance, it can be said that when students feel that SNS are compatible with learning, they will conclude that these networks will also increase their academic performance. In addition, the results showed that, if students believed that SNS performed their job tasks well enough, they would find them equally useful for learning.

The relationship between SN with Image and PEU with PU was also confirmed. These are consistent with the findings of Al-gahtani (2016) and Müller (2013). Accordingly, accepting the others opinion regarding the use of SNS can improve the status of students among their classmates or professors. In addition, if the use of SNS in education and learning is easy for students and does not require a lot of time to learn, it will be equally useful for their education. The findings indicated that RES had no significant impact on PU, which is consistent with the findings of Al-gahtani (2016), and it is incompatible with the findings of Binobaid (2017). Respondents probably believe that the results of using SNS in education are not tangible and visible. Among the determinants of perceived usefulness, SN was the strongest indicator. This indicates that students value the opinions of others (probably their professors) regarding the practicality and usefulness of SNS in education. Therefore, professors can play an important role in attracting students' attention to the use of SNS.

Results also showed that four constructs including SE, ANX, PL, and ENJ were determinants of Perceived Ease of Use. The findings of Binobaid (2017), and Jeffrey (2015) help confirm these results. This means that students who have higher SNS self-efficacy will perceive more ease of use about SNS. The findings also showed that computer anxiety was the only variable that was negatively related to perceived ease of use. Students who are negative and anxious about using computer technology believe that using SNS is not easy and requires time to learn. Also, according to the results, students who feel comfortable using computer technology, using SNS is not difficult for them. Finally, when students enjoy using SNS, they have no problem working with it and it will be easy for them to use it. Among these constructs, SE is the best predictor of PEU, which is consistent with the findings of Abdullah and Ward (2016).

Indicators of Behavioural Intention were SN, PU, and PEU, which is compatible with the findings of Dumpit and Fernandez (2017), Moorthy *et al*. (2019), and Owusu *et al*., (2019). The more students find the use of SNS useful in education and learning, the more they feel that using these networks can increase their ability to learn, and the more serious their decision to use this technology will be. Also, the easier it is for students to use SNS in education, the more they will intend to use it. Results showed the PU was the strongest predictor of Behavioural Intention (consistent with Venkatesh and Bala, 2008). However, in Al-Gahtani's (2016) study, the strongest factor was the Subjective Norm. Given that Al-Gahtani tested this model in the field of e-learning in Arabic culture, it can be concluded that the results of the present study are closer to western culture (the original culture of the TAM 3 model) than Arabic culture. This also differs from the findings of Cheung and Vogel, 2013; Kwon and Wen, 2010). It seems that because students are very familiar with SNS and have no difficulty in using them, the usefulness of these networks in the educational context is more important to them for the acceptance process. This issue highlights the need to pay attention to the type of SNS being utilized and its capabilities for use in education.

Results showed that Behavioural Intention had a significant positive impact on Use Behaviour. This finding is consistent with the findings of Dumpit and Fernandez (2017) but rejects Müller's (2013) findings. Thus, if students can help make decisions when it comes to how to best use SNS for educational purposes, this decision will lead to real use and can better impact their performance.

Finally, according to the findings, Use Behaviour had a significant positive effect on Academic Performance. This is compatible with the findings of Lambić (2016), Moorthy *et al*. (2019), and Manca and Ranieri (2013), but incompatible with the results of Giunchiglia *et al*. (2018) and Liu *et al*. (2017). According to this finding, more and better use of these media by students in the educational system can cause tangible results in improving their academic performance.

CONCLUSIONS

Contrary to opinions that regard SNS as more suitable for communication opposed to learning and teaching support (e.g., Lacka and Wong, 2021), this work suggests that agricultural students who use SNS for education purposes have better academic performance than those who do not. This is a significant result for agricultural colleges to consider and explore in future research as academics and administrators seek creative alternatives to engage students to help them achieve their academic intentions as they work towards their future achievements—especially as the world and employment opportunities are increasingly virtual and digital. It is important to have an open mind about the use of SNS in teaching and learning. Professors and administrators of agricultural colleges should emphasize the creative and unbiased use of these networks, as they provide opportunities for improved education, reduced costs, and broad participation. According to the explicit results of this study and a discussion of previous studies on the potential of SNS in agricultural education and learning, more research is needed. For instance, due to neglect among components of agricultural education systems, higher education policymakers, managers and educational planners should try to include and make these networks more accessible in the agricultural curriculum. So, this study could open up new horizons for agricultural academic administrators, strategists, and faculty members who seek to engage students in technology as they expand educational opportunities and achieve their intentions. Importantly, providers across the agricultural education system can use these study results to improve the efficiency across this system.

There is a need for educators within the agricultural education system to state clearly the importance of using educational media. This can be achieved by creating specific and defined incentives. In this regard, it is suggested that blended learning methods be included with formal teaching methods in agricultural courses so that professors are required to provide part of the lesson using SNS. Only then can students use these networks to reach learning goals. If the agricultural education system can use the capabilities of this technology in teaching and learning, it will not lag behind the advancement of technologies in other fields of study. This will facilitate and accelerate learning for students and will make students more motivated to learn in a way that they like themselves, and pay at the time and place they prefer. As mentioned in the introduction, institutionalizing the use of social networks for part of agricultural education (mostly for the theoretical part of the course) provides an opportunity to focus on face to face skills training.

According to previous research (e.g., Dastani *et al*., 2019), the most popular and most used SNS platform by Iranian students is Telegram, but this platform is filtered in Iran and is not easily accessible. This and other issues can affect the rate of using SNS in education by students and faculty members. Further studies can investigate the impact of such structural issues. A limitation of this study is that we did not examine the differences between the agricultural disciplines because some disciplines of agriculture are practical and others are theoretical and may vary in their acceptance and use of SNSs in education. Therefore, this is a consideration for future studies in other disciplinary areas. Furthermore, this study did not consider the educational level variable in the model, whereas acceptance and use rates may vary at different levels of education. Future studies will examine the effect of these two factors.

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تأثیر شبکه های اجتماعی بر یادگیری: توسعه مدل TAM 3 برای ارزیابی عملکرد تحصیلی در آموزش عالی

س. ا. برآبادی، ع. شمس، و ن. وایس

چکیده

بررسی قابلیت های شبکه های اجتماعی در آموزش و یادگیری می تواند در آموزش عالی مفید بوده و به بهبود عملکرد دانشجویان کمک کند. این مطالعه عوامل موثر بر پذیرش و استفاده آموزشی از شبکه های اجتماعی و تأثیر این استفاده بر عملکرد تحصیلی را با استفاده از مدل پذیرش فناوری ۳ بررسی می کند. ۴۰۰ دانشجوی کشاورزی در مطالعه شرکت کردند و داده ها از طریق مدل سازی معادلات ساختاری مورد تجزیه و تحلیل قرار گرفتند. نتایج نشان داد که هنجار ذهنی، تصویر، ارتباط شغلی و کیفیت خروجی پیش بینی کننده «سودمندی درک شده» بودند. پیش بینی کننده های «سهولت استفاده درک شده» نیز شامل خودکارآمدی، اضطراب، سرگرمی و لذت درک شده بودند. یافته ها نشان می دهد که سودمندی درک شده و سهولت استفاده درک شده، تأثیرات قابل توجهی بر قصد استفاده از شبکه های اجتماعی و قصد رفتاری نیز تأثیر قابل توجهی بر استفاده واقعی داشته است. در نهایت مشخص گردید که استفاده آموزشی از شبکه های اجتماعی تأثیر مثبت قوی بر عملکرد تحصیلی دانشجویان دارد.