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A Triarchic Model on Student's M-Learning Readiness in the Omani Context: A Structural Model View

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Abstract

The purpose of this study is to investigate the effects of personal, environmental, and technological factors on college students' behavioral intention towards m-learning in the Omani context. Two hundred seventy students from the College of Applied Sciences-Sur in Oman participated in the study. A triarchic latent model with mediational effects through the technological factor on m-learning readiness is proposed based on the literature. The results indicate that a direct model without any medication effects fits the data better. The three factors collectively explained over half of the variances on readiness. Among the three factors, the technological factor represented by perceived usefulness and perceive ease use demonstrated the largest effect of 26%, followed by the personal factor in term of computer self-efficacy and grit at almost 17%, and then the environmental factor of social support and organizational facilitation at approximately 11%. This research provides a direction for further studies on hypothesizing and testing other latent models of m-learning readiness. The findings also have practical implications.

Keywords: Higher education; Improving teaching/learning; readiness for mobile learning; M-learning adoption; mobile education

Perspectives and Theoretical Framework

Over the past several decades, the application of information and communication technologies (ICT) in higher education has evolved from flexible learning, e-learning, to m-learning. M-learning is a newest mode of e-learning and distance learning. It refers to any learning that utilizes wireless mobile devices such as smart phones, tablet PCs, PDAs, and the like [1]Peters[2] in 2007 defines m-learning as the 'just enough, just in time, just for me' model of flexible learning, and further depicts its relationships with e-learning and flexible learning as in Figure 1. It is largely a subset of e-learning. Both are subsets of the broader flexible learning or distance learning. It should be noted that m-learning is not fully a subset of e-learning as some parts of m-learning are beyond the boundary of the latter.

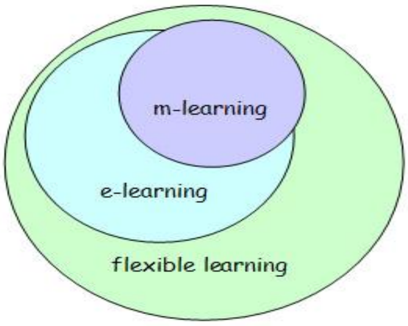

Fig. 1.The 'just enough, just in time, just for me' model of flexible learning [2].

Mobile technology has been prevalent in the past two decades, possibly because it has gradually become easier to use and more affordable, effective, and powerful [3]. It has been predicted that mobile technology will continue to grow in its power and capacities [4]. M-learning has demonstrated the advantages over the traditional and e-learning methods on promoting collaborative learning and prompting just-in-time feedback [5]; [1]; [6]. Most likely, m-learning will continue to play a vital role in higher education in the future due to its convenience, flexibility, capacity, and promptness [7, 8].

The Sultanate of Oman has set a national policy to embrace mobile and digital technology since 2014. Digital technologies and wireless networks have undergone rapid growth recently in Oman. Mobile devices have been pervasive on the Omani university campuses. However, m-learning in higher education in Oman is still in its infancy. Many colleges have not implemented m-learning yet. The purpose of the present study is to explore students' status of readiness on m-learning and the influential factors in the context of Omani higher education.

M-learning in Oman

The Omani government has shifted its focus from the energy industry towards a service one to support sustainable economic growth through knowledge and expertise of technologies [9].The government has clearly stated that ICT is a key priority in promoting the Omani businesses in the international arena. Furthermore, the Information Technology Authority of Oman in 2017 delivered the 2030 Digital Oman Strategy (e-Oman) focusing on development of IT skills, digital literacy and modern technologies. Meanwhile, the Omani IT operators have also made huge steps forward, moving beyond infrastructure to developing applied business solutions. The Omani people has been passionate about the digital and mobile technologies as well. By the end of April 2017, Oman's mobile phone subscriber base had crossed 7 million, with a penetration rate of more than 150 per cent ("Oman's mobile phone subscriber base crosses 7 million", 2017). At the end of 2017, the number of internet users was over 3.3 million, a 68.5% penetration rate which is 4% higher than the average for the middle east and 14% higher than the worldwide. On social media, the penetration rate had reached to 43% by October 2017, next to the highest rate of 59% for Saudi Arabia in the Middle East. Moreover, by December 2017, the Facebook subscribers had dramatically increased to 2,630,000 in just two months, a penetration rate of 54.5%. Oman also has the highest rate of Twitter access through mobile devices in the Arab world. The Omani Twitter users generate 500,000 - 600,000 tweets per day. Interestingly, 90% of the time they access Twitter via mobile phones, 10 % higher than other GCC countries. It seems that the Omani tend to handle every task with their mobile devices if ever possible ("Oman's mobile phone subscriber base crosses 7 million", 2017).

Nevertheless, in contrast to the government's strong endorsement on ICT and people's passion about mobile technology, the education sector in Oman has remained relatively insulated, largely due to the financial cutbacks. The recent reductions in public education has created new opportunities for private participation especially from foreign entities. The international interest seems to be fueled by both Oman's sizeable youth population and the government's continued focus and support on attaining a knowledge-based and diversified economy but the picture of m-learning in the private sector is still blurred currently.

M-learning at College of Applied Sciences,

The Sur College was founded in 1987. The purpose of its establishment was to prepare students ready for teaching elementary and junior high schools. In 2007, six colleges, including the Sur College had formed the Colleges of Applied Sciences (CAS), the only ones which fall under the Ministry of Higher Education in the country. The College of Applied Sciences-Sur offers bachelor's degrees in four programs: information technology, design, communication studies, and applied biotechnology.
CAS-Sur in Oman has adopted a mixed model of teaching and learning, a combination of the traditional face-to-face and the online or e-learning approaches. Whereas significant campus attendance remains, online activities such as access to the course materials, discussion, assessment, and collaborative team work have been an integral part of course work and requirement [10]. These e-learning activities mainly have taken place within two learning management systems (LMS): Blackboard (merged with WebCT) and the Modular Object-Oriented Dynamic Learning Environment (Moodle). Blackboard is a platform designed to enable innovative education activities happening everywhere by connecting people and technology. Moodle is an open source developed for online course management system. It allows students and teachers to overcome the barriers of the traditional classroom by building an electronic classroom on the web [11]. In addition to the two LMS, there are other modern technological and electronic systems on campus as well - the student information system (SIS) for online admission and registration, the symphony library management system, a web-based e-mail system, and an e-Journals database service (EBSCO) to support research ("The Student Guide for the Academic Year 2017-2018", 2018). However, m-learning has not been officially implemented on campus yet.

The Models of M-learning

Since ICT has played a key role in education, various theoretical models have been proposed to explain the user acceptance behaviors. Among them, the Technology Acceptance Model (TAM) [12], the Theory of Planned Behavior (TPB) [13], and the Unified Theory of Acceptance and Use of Technology (UTAUT) [14] were relatively popular. Each model has its unique focus and proposes a distinct set of salient factors that influence acceptance of technology.
TAM proposes two components of behavioral intention: attitude towards behavior and perceived usefulness [12]. It posits that positive attitude and high perceived usefulness more likely result in high behavioral intention and actual behavior eventually. It further claims that attitude, which is defined as the emotional state toward using a technology [15], is influenced by the beliefs of perceived usefulness and perceived ease of use. TPB, developed to explain human behavior in general, emphasizes the importance of social norm, that is, a person's perception of the social norm pressure from the significant ones. UTAUT, another model specifically focusing on technology acceptance. also stresses the critical role of social influence, a term akin to subjective norm in TPB. In addition, UTAUT postulates that facilitation condition in terms of organizational support and technical infrastructure is also a key determinant. In Davis's TAM, computer self-efficacy is not a separate factor. Instead, it is one of the mechanisms of perceived ease of use to affect attitude [16]. In the Technology Satisfaction Model (TSM), [17] proposed that computer self-efficacy is independent of perceived ease of use. It is surprisingly found that few empirical studies have been conducted to explore the relationship between grit, a newly explored personal trait, with acceptance of technology [18]. Grit is defined as a personality trait of perseverance and passion for long-term goals [19]. It is related to personal intrinsic motivation in a continuous way to overcome the adversities and to pursue the goal. It is not a cognitive characteristic of mental capacity. It also distinguishes

itself from other personal traits such as conscientiousness, need for achievement, or self-control in its stamina in the pursuit of long-term objectives, whereas the other traits do not necessarily involve such long-lasting goals [19], Peterson, Matthews, & Kelly, 2007). Very limited studies have shown that it reliably predicts positive outcomes of e-learning e.g [18].

Other models attempted to integrate some of the theoretical constructs mentioned above. For instance, based on Bandura's social cognitive theory (SCT), Wang and Lin in 2007[20] proposed a model with three reciprocal interactive factors (Figure 2) to understand students' web-based learning behaviors: personal, behavioral, and environmental. Liaw and Huang (2015) modified Wang and Lin's bidirectional model to a one-way three-tier model in examining how factors of personal attitudes and learning environments affect gender difference toward mobile distance learning acceptance (Figure 3). Many path analysis studies have proposed and tested various mediation models to understand behavioral intention towards m-learning or e-learning (e.g., [21]; [22-24]; [14, 25], but none have been found to use a latent model approach.

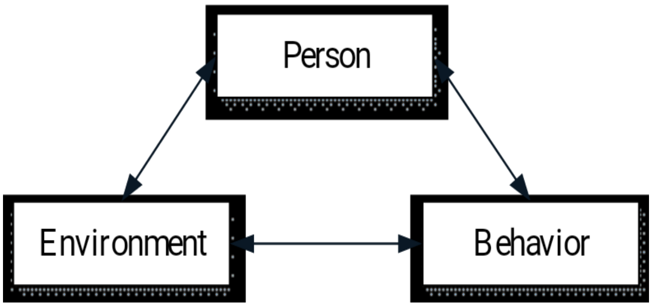

Fig.2. Social Cognitive Theory [20].

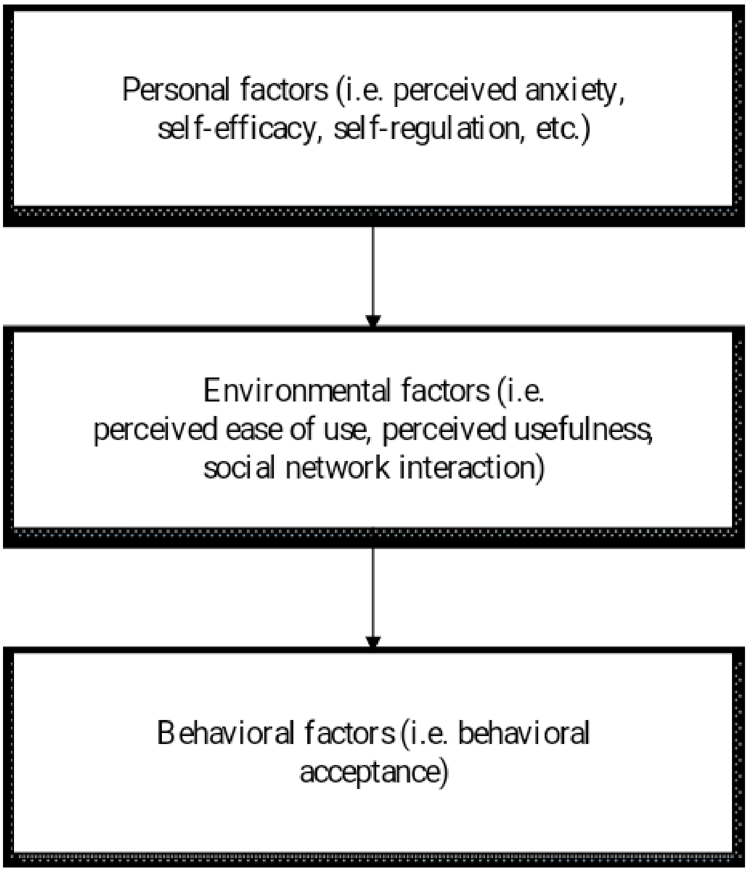

Fig.3.The three-tier model [26].

Based on the literature review, the present study takes a step further by incorporating grit as a critical component of personal factor and develops a model on students' m-learning readiness as in Figure 4. It should be noted that, in the proposed model, in addition to the direct effects of personal, environmental, and system or technological factors on behavior, there are indirect effects of personal and environmental factors via the technology factor as well. However, personal and environmental factors are treated as two independent entities. Also, as the College of Applied Sciences-Sur has not implemented an m-learning system yet, the behavioral factors focus on behavioral intention only in this study.

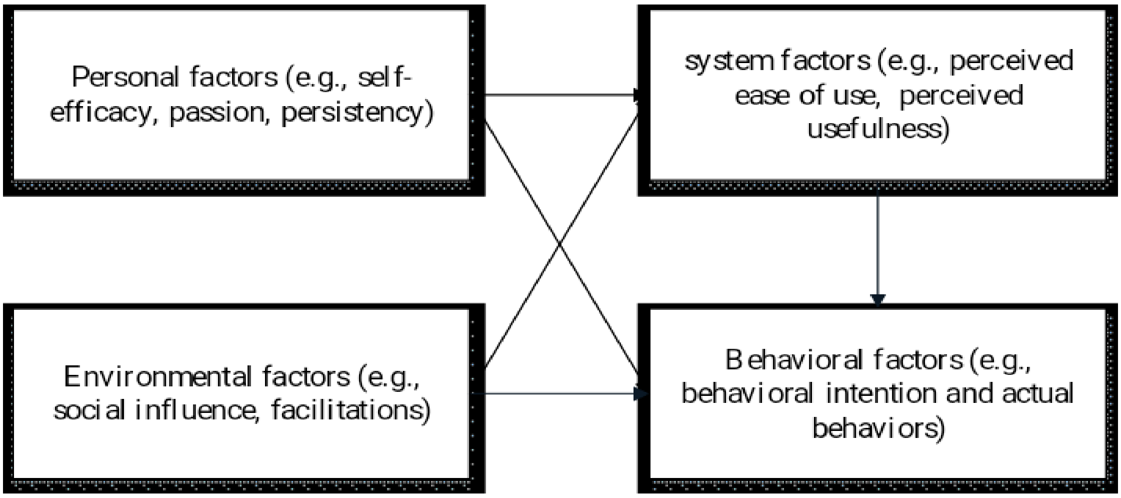

Fig.4.The research model

The constructs from other studies in the above model are further delineated in Table 1. It is interesting to note that although grit is defined as passion and perseverance for long-term goals, passion and perseverance themselves have not specifically defined[19]. The definition of these two constructs are obtained elsewhere. With the specifications in Table 1, the conceptual model in Figure 4 is further operationalized as a research model shown in Figure 5.

Table 1Definition of the Studied Constructs

Theory	Theoretical Constructs	Definitions
Technology Acceptance Mod (TAM)	Attitude Toward Behavio	"An individual's positive or negative feelings (evaluative affect) about performing the target behavior" [15].
	Perceived Usefulness	"The degree to which a person believes that using a particular system would enhance his or her job performance" [12].
	Perceived Ease of Use	"The degree to which a person believes that using a particular system would be free of effort" [12].

Theory of Planne Behavior (TPB)	Behavioral Intention	“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.” [13].
	Subjective Norm	“The person’s perception that most people who are important to him think he should or should not perform the behavior in question” [15].
Unified Theory of Acceptance and U of Technology (UTAUT)	Social Influence	“The degree to which an individual perceives that important others believe he or she should use the new system [14].
	Facilitating Conditions	“The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system” [14].
Grit	Passion	“a strong inclination toward a self-defining activity that one loves, values, and in which one invests a substantial amount of time and energy” [27].
	Perseverance	“to try to do or continue doing something in a determined way, despite difficulties” (Cambridge Dictionaries Online)

In the research model, computer self-efficacy [17] and passion and perseverance of grit [19] are selected to represent the latent personal variable. Social support or social network support [14, 15] and organizational and architectural facilitation [14] are chosen for the latent environmental factor. The technology or system factor concentrates on perceived ease use and perceived usefulness [12]. The latent dependent variable, behavioral intention, has two components: an attitudinal dimension and a rational dimension. Attitude indicates a person’s evaluative affect about performing the target behavior [15]. In fact, Azjen and Fishbein (1975) further stated that attitude contains two separate constructs actually: attitude towards the objects and attitude towards the behavior. The attitudinal construct used in this study apparently focuses on the one towards behavior. Accordingly, the last observed variable, intent, represents people’s rational judgement on how hard they are willing to perform the behavior [13].

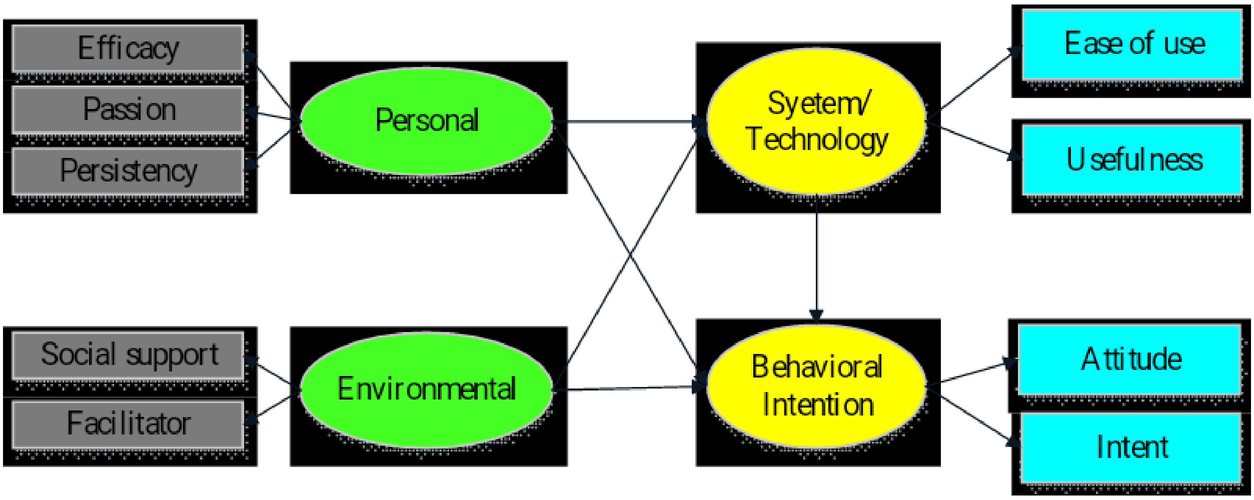

Fig. 5.The hypothesized research model

M-learning Studies in the Omani Higher Education Context

The mixture of the traditional face-to-face model and e-learning has chiefly characterized Omani higher education for the past decade. The technological backbones of e-learning are the two LMSs: Blackboard and Moodle. M-learning has not taken place at the national level or in a large scale. Nevertheless, some research and practices on m-learning targeting on the Omani college students have been reported. These studies mainly fall into three categories: investigating the current statuses of m-learning and peoples' attitude towards m-learning including relevant measurement instrument development and validations (e.g., [28, 29]; [30-34], theoretical and conceptual exploration of m-learning in the unique Arabic culture (e.g., [35-37]), and applications of mobile technologies in the existing e-learning system (e.g., [37-42]).
The present study belongs to the first category, focusing on students' readiness on m-learning. It differs from the existing research on its testing of a latent model. It aims at identifying the impacts of the critical personal, environmental, and technological factors on students' behavioral intention towards m-learning. It is also the first of its kind to include grit as part of the prediction model.

Purpose of the study, Hypotheses, and Research, Question

This study was designed to explore how the personal, environmental, and system or technological factors interact with one another to influence readiness of m-learning in college students in Oman. A latent model with three independent variables and one dependent variable was formulated and tested. More specifically, the main research questions were:
1. Does the personal factor, represented by computer self-capacity and grit, influence m-learning readiness defined by behavioral intention?
2. Does the environmental factor in term of social influence or social norm and facilitating conditions impact m-learning readiness?
3. Does the system or technological factor characterized by perceived ease use and perceived by usefulness relate to m-learning readiness?
4. How does the personal factor mediate m-learning readiness through the system factor?
5. How does the environmental factor mediate m-learning readiness through the system factor?
Accordingly, the hypotheses that were tested in this study are given below:
H1: The personal factor has a significant direct effect on behavioral intention.

H2: The environmental factor is a salient predictor of behavioral intention.
H3: The system factor directly predicts behavioral intention significantly.
H4: The personal factor has a significant indirect effect through the system factor on behavioral intention.
H5: The environmental factor significantly predicts behavioral intention through the system factor.

Methods

Research Participants

The survey was distributed to 327 students at the College of Applied Sciences-Sur in January 2018. Two hundred and seventy-three returned the survey, at a response rate of nearly 83%. Three of them had invalid data. The final sample of 270 students consisted of 78 males and 192 females (see Table 2). Almost 63% of the participants were 21 years old and below. About 29% of the sample were between 22 and 15, and the remaining were 26 and above. Regarding the majors of the participants, approximately 39% were in information technology, 43% in mass communications, and the rest in applied bio-tech.
Table 2 also shows that almost every student had a smart phone and a notebook or laptop. Also about half respondents owned a notebook or laptop, comparing with only 37% participants owning a traditional desktop or personal computer. About one fifth students had a portable music or video player, and one tenth owned a netbook or an e-book reader. Mobile phone had been almost completely replaced by smart phone, leaving its ownership rate at only 6%. Finally, PDA became the least owned mobile device in the sample, at 4% only.

Table 2The Sample's Profile (N=270)

Variables	Frequency	Percentage
Gender		
male	78	29
female	192	71
Age group		
21 and below	169	62.6
22-25	79	29.3
26 and above	22	8.1
Major		
Information technology	106	39.3
Mass communications	116	43.0
Applied bio-tech	48	17.7
Devices owned		
Smart phone (such as iPhone)	262	97%
Notebook or Laptop	259	96%
iPad or other tablets	132	49%

Desktop Computer/Personal Computer	100	37%
Portable Music/Video Player (e.g. iPod)	51	19%
Netbook	30	11%
E-book reader	24	9%
Mobile phone	16	6%
Personal Digital Assistant (PDA)	11	4%

The Observed Variables and the Measurement Instrument

The survey, adopted from benchmark works conducted in the West and other Arabic countries, consists of seven parts (see Appendix A). Part 1 collected some demographic data, and part 2 investigated what types of popular mobile devices the participants own. Part 3 explored participants' familiarity with the popular mobile application, and part 4 was interested in how often students utilized the mobile devices for course work and personal or social needs. Part 5 was a single-item question inquiring how soon the students expected the implementation of m-learning on campus. Part 6 focused on the measurement variables of computer self-efficacy, perceptions of social support and facilitation, perceived ease use and perceived usefulness of mobile technology, attitude towards m-learning, and behavioral intention to use m-learning. These items, with some wording modifications, were devised from similar tasks (e.g., [23, 33, 43-45]); Each item had five rating points: 1 = *Strong disagree*, 2 = *Disagree*, 3 = *Neutral*, 4 = *Agree*,and 5 = *Strongly Agree*. The negatively worded items were reversely coded. Some initial items were eliminated in the process of exploratory factor analysis due to weak or cross factor loading. The remaining 31 items are clustered as follows: computer self-efficacy (4 items), perceived social network support (5 items), perceived facilitation (4 items), perceived usefulness (5 items), perceived ease of use (5 items), attitude (4 items), and behavioral intention (4 items). The last part was the 8-item Short Grit Scale (Grit-S) from [19] without any modification. The 5-point Likert Grit-S Scale has two subscales: passion and perseverance. The items were rated as 1 = *Not like me at all*, 2 = *Not much like me*, 3 = *Somewhat like me*, 4 = *Mostly like me*,and 5 = *Very much like me*.

Result

Online Applications and Mobile Devices

The respondents were asked to report their usage frequencies on 10 popular mobile applications. A 5-point Likert scale from "1=Never use" to "5=Very often" was used (see Table 3). Among the ten online tools, YouTube was the one mostly used. Nearly 78% respondents used it often or frequently. The other three mobile applications with a usage rate over 50%, by combining the choices of "Often" and "Very often," were Wikipedia, Google Docs, and Facebook at 64.7%, 62%, and 60.2%, respectively. On the other hand, WhatsApp, Khan Academy, LinkedIn, and Academia.edu were the four least frequently used applications with a combination rate of 21.2%, 13.9%, 12.0%, and 11.8%, respectively. About one third participants reported using Twitter and Instagram at a regular or frequent basis.

Table 3Use of Online Applications (N = 270)

Online Applications	Never use	Occasionally	Sometimes	Often	Very often
YouTube	1.9%	5.2%	15.2%	33.7%	44.1%
Twitter	35.4%	15.6%	13.4%	22.0%	13.2%
Facebook	22.6%	11.7%	15.3%	18.7%	31.5%
WhatsApp	44.4%	28.2%	6.2%	8.9%	12.3%
Wikipedia	5.2%	10.7%	19.4%	30.4%	34.3%
Google Docs	16.5%	10.9%	10.6%	26.8%	35.2%
Instagram	34.8%	23.7%	7.6%	18.9%	15.0%
LinkedIn	48.5%	30.2%	9.3%	7.4%	4.6%
Khan Academy	50.2%	26.5%	9.4%	8.1%	5.8%
Academia.edu	53.2%	26.2%	8.8%	7.8%	4.0%

For the purposes of using mobile devices, nearly half of respondents reported they sometimes uses the technology for the course-related learning (see Table 4). About one fifth students never or occasionally use mobile devices for course work. On the other hand, one eighth respondents used the tools for academic learning at a regular or frequent basis. For none-course-related personal needs, eighty percent of the respondents reported a frequency of 'Often' or 'Very often,' indicating students often or frequently used the mobile tools to meet their non-learning needs. Another 20% reported a rare or light use of mobile devices.

Table 4Purpose of Using Mobile Device (N = 270)

Online Applications	Never use	Occasionally	Sometimes	Often	Very often
Course-related learning	0.9%	25.2%	48.2%	13.3%	12.4%
Other needs	0.4%	8.8%	10.4%	32.8%	47.6%

When the respondents were asked to indicate how soon they expected an implementation of m-learning on campus, almost half preferred to see it between six months and one year. Thirty percent expected to use it within six months. Seventeen percent of students even liked to use m-learning immediately, and only 4% of the participants hoped m-learning to be implemented one year later.

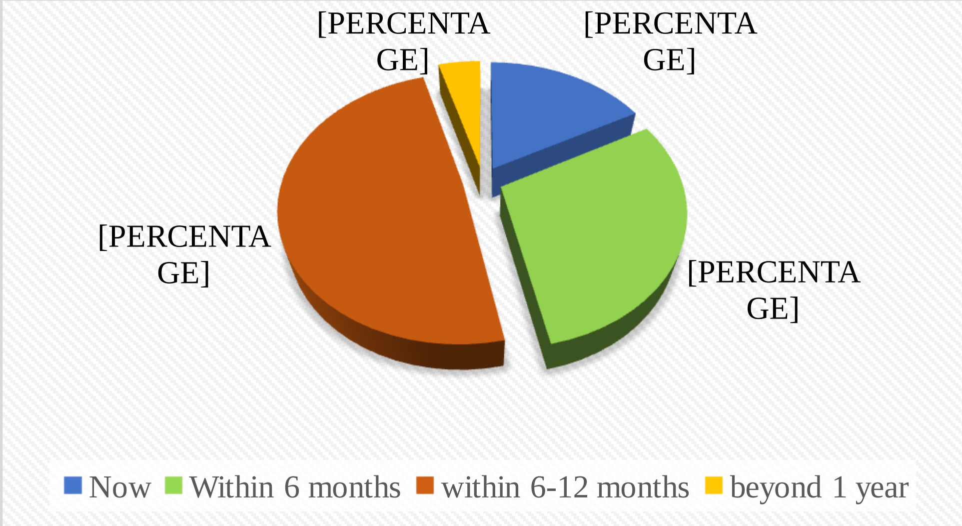

Fig.6. The Expected Timeframe of Implementation of M-learning on Campus

Measurement Model

Exploratory factor analysis, using the method of principal components extraction with varimax rotation, was conducted initially using SPSS 23. After several items with weak or cross loading were eliminated, the remaining 31 items on Table 5 loaded on seven factors. The results showed that all items fitted onto their respective factors well. The internal consistency reliability coefficients in Cronbach's alpha for the seven observed variables satisfactorily ranged from .80 for perceived social support to .93 for behavioral intent.
Table 5 also shows the factor means and standard deviations, along with the item mean and standard deviation. The factor means ranged from 3.08 for perceived facilitation to 3.65 for computer self-efficacy, and all were on the positive direction. The two environmental variables had the lowest means of 3.08 and 3.11, whereas computer self-efficacy, attitude, and behavioral intent scored relatively high at 3.65, 3.58, and 3.51, respectively.

Table 5Mean (Standard Deviation) and Cronbach Alpha for the Seven Observed Variables (N = 270)

Construct	*Item*	*Loadings*	*M(SD)*	*Alpha*
Computer self-efficacy (CSE)			3.65(0.9)	0.86
	1. I feel capable of using mobile technologies	.875	3.82(.92)	
	2. I can easily save and print learning materials using wireless internet	.782	3.43(.86)	
	3. I can download the needed software using wireless devices.	.862	3.71(.93)	
	4. I am competent on online shopping using wireless internet.	.745	3.67(.91)	

Perceived usefulness (PU)			3.43(.93)	0.88
	5. Using mobile technologies increases my chances of achievement.	.864	3.20(.88)	
	6. Mobile technologies help me accomplish my tasks more quickly.	.784	3.28(.90)	
	7. Mobile technologies make more productive in accessing to educational resources.	.853	3.32(.91)	
	8. I find mobile technologies useful in my daily life.	.905	3.76(.98)	
	9. Mobile technology can offer new opportunities for communication and team-working.	.816	3.42(.94)	
Perceived ease of use (PEU)			3.28(.90)	.84
	10. I find it easy to get the information through the Blackboard learning system using wireless internet	.873	3.59(0.95)	
	11. I find mobile devices are flexible and easy to use.	.900	3.12(.86)	
	12. Learning to operate mobile technologies does not require much effort for me.	.754	3.15(.87)	
	13. My interaction with mobile technologies has been easy so far.	.782	3.40(.99)	
	14. It would be easy for me to become skillful in using an m-learning system.	.791	2.98(1.13)	
Perceived social support (PNS)			3.11(.92)	.80
	15. People who mostly influence me think that I should use mobile technologies.	.734	3.09(.94)	
	16. My friends and classmates have utilized mobile technologies in their studies.	.823	3.06(.96)	
	17. People whose opinions that I value prefer me to use mobile technologies more.	.794	3.13(.87)	
	18. It seems that my lecturers are not interested in integrating mobile technologies into their teaching practices.	.823	3.08(.87)	
	19. Our college does not support mobile technologies.	.802	3.25(.86)	
Perceived Facilitation (PF)			3.09(.96)	.81
	20. I have the necessary resources to	.734	3.23(.99)	

	utilize mobile technologies.			
	21. I have the necessary knowledge and skills to take advantage of mobile technologies.	.836	3.03(.95)	
	22. Mobile technologies are compatible with other digital technologies I have used.	.758	3.01(.85)	
	23. I can get help from others if I have difficulties in using mobile technologies.	.812	3.18(1.02)	
Behavioral Intent (BI)			3.51(.92)	.93
	24. I plan to use mobile technologies more in my future studies.	.923	3.67(.96)	
	25. I do not intend to use m-learning.	.789	3.45(.88)	
	26. If I have a choice, I prefer the traditional face-to-face way to m-learning.	.824	3.14(.855)	
	27. I am eagerly expecting to the forthcoming m-learning on campus.	.914	3.57(1.03)	
Attitude (ATT)			3.58(.96)	.92
	28. I am not enthusiastically about m-learning.	.785	3.42(.96)	
	29. Using m-learning is a wise idea.	.823	3.67(.93)	
	30. I dislike the idea of using m-learning.	.708	3.61(.98)	
	31. Mobile learning is nothing more than a fashion in education.	.793	3.45(.92)	

Note: 5-point Likert scale with 1 = strongly disagree and 5 = strongly agree.

Similarly, exploratory factor analysis was performed on the 8-item Short Grit Scale [19]. The items loaded on the two factors as expected. The Cronbach alphas were satisfactory at .83 for passion and .87 for perseverance (see Table 6). Both means were greater than 3.0, implying that the respondents were passionate and perseverant towards long-term goals. The mean on perseverance was slightly higher than that on passion.

Table 6Mean (Standard Deviation) and Cronbach Alphas for the Short Grit Scale (N = 270)

Construct	*Item*	*Loadings*	*M(SD)*	*Alpha*
Passion (PA)			*3.07(.94)*	

				.83
	1. I often set a goal but later choose to pursue a different one.	.645	3.18(.96)	
	2. New ideas and projects sometimes distract me from the previous one.	.617	3.14(.89)	
	3. I have been obsessed with a certain idea or project for a short time but later lost interest.	.585	3.05(.93)	
	4. I have difficulty maintaining my focus on projects that take more than a few months to complete.	.672	2.86(.92)	
Persistence (PE)			3.26(.95)	.87
	5. I finish whatever I begin.	.687	3.29(1.1)	
	6. Setbacks don't discourage me.	.654	3.17(.92)	
	7. I am a hard worker.	.723	3.35(.98)	
	8. I am diligent.	.718	3.28(.93)	

Note: 5-point Likert scale with 1 = Not like me at all and 5 = Very much like me.

Structural Model

To test the research model in Figure 5, the inter-factor correlations among the nine observed variables were first obtained and presented in Table 7. All coefficients were significantly at the .001 level. Next, the hypothesized model in Figure 5 was tested with the maximum likelihood approach in Lisrel 8.8, and the output was presented in Figure 6.

Table 7Inter-factor Correlation Matrix (N=270)

	PA	PE	CSE	PNS	PF	PU	PEU	BI	ATT
PA	1								
PE	.80	1							
CSE	.81	.83	1						
PNS	.42	.48	.46	1					
PF	.44	.46	.44	.81	1				
PU	.45	.42	.43	.39	.40	1			
PEU	.52	.45	.49	.41	.38	.82	1		
BI	.51	.52	.48	.46	.45	.55	.52	1	
ATT	.50	.49	.46	.42	.41	.53	.50	.80	1

Note: a. PA – Passion, PE – Perseverance, CSE – Computer Self-efficacy, PNS – Perceived Network Support, PF – Perceived Facilitation, PU – Perceived Usefulness, PEU – Perceived Ease of Use, BI – Behavioral Intent, and ATT – Attitude.b. All the correlation coefficients were significant at the .001 level.

Figure 6 indicates that the hypothesized model was validated in the present sample: χ^2 (21, N = 270) = 27.99, p = .140, and RMSEA= .035 (0.0, 0.066). The other statistical indexes also demonstrated a good fit between the model and the data: GFI = .98, AGFI =.95, CFI =1.00, NFI = .99, NNFI=1.00, and SRMR =.018. The reliability coefficients, obtained from EQS 6.4, were satisfactory as well, with a value of .858 in Cronbach alpha and .827 in Raykov's Rho.

Secondly, the results showed that all factor loadings on the measurement models were significantly at the .001 level, with standardized structural coefficients between .87 to .92. For the statistics between the latent variables shown on the diagram, the first number in parentheses was the unstandardized structural coefficient, and the second number was the standardized structural coefficient. The third one in the parentheses was the correlation coefficient between the latent factors, which was transformed in SPSS from the covariance matrix provided by Lisrel. The last one below the coefficients was the corresponding t-value. Figure 6 shows that all path structural coefficients were statistically at the .001 level, except the one from the environmental factor to the endogenous behavioral intention at the .01 level.

Thirdly, the three latent independent variables collectively explained 53% of the variance on the endogenous behavioral intention. Additionally, the personal factor and the environmental factor together accounted for 36% of the variance on the technology factor as well. Moreover, all the structural coefficients on the diagram were statistically significant at the .001 level, except the one from the environmental factor to behavioral intention at the .01 level.

In addition to the direct effects, the personal and environmental factors also had indirect effects through the technology factor. The Lisrel output showed the indirect effect for the personal effect was .16 (i.e., the product of the unstructured coefficients .42 and .38), whereas the direct effect was .26. The indirect effect between the environmental factor and behavioral intention through the technology factor was .09 (i.e., the product of the two unstructured coefficients .23 and .38), whereas the direct effect was .17.

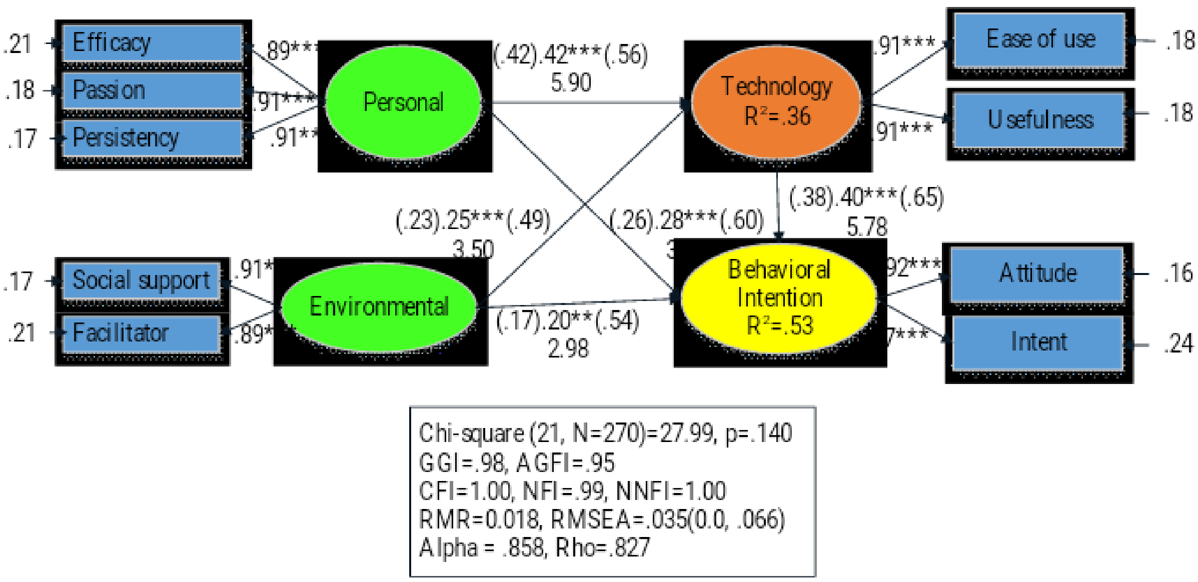

Fig.7.Maximum likelihood estimation of the hypothesized model with mediation effects.

Finally, to further examine the effect sizes of the direct and indirect effects of the personal and environmental factors on behavioral intention, the mediation paths through the technology factor were removed, and the alternative model was tested again. Interestingly, the new parsimonious model without any mediation effects demonstrated almost identical results as the previous one as in Figure 7, except for the factor loading of perceived ease of use down to .90 from .91. These results implied that the indirect effects of the personal and environmental factors on behavioral intention through the technology factor in fact contributed little to the variation on behavioral intention. Thus, the model with direct effects only in Figure 7 was apparently better than the one in Figure 6 with indirect effects, and thus chosen as the final model. In this model, the three latent independent variables collectively accounted for 53% of the variance on the latent dependent variable. The technological factor contributed the most at 26%, followed by the personal factor at approximately 17%, and both were significant at the .001 level. The environmental factor explained the remaining 11%, statistically significant at the .01level. The first three hypotheses were supported, whereas the last two on the indirect effects were rejected.

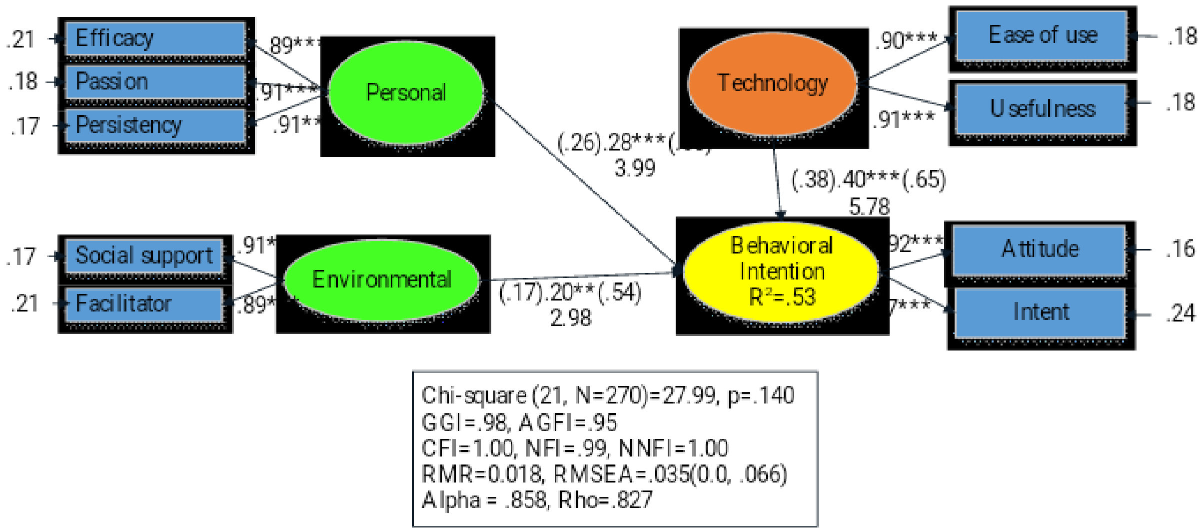

Fig.8. Maximum likelihood estimation of the research model without a mediation effect.

Discussion

The present study found that nearly every student owns a smart phone and a notebook or laptop nowadays. This finding is consistent with other studies recently conducted in the Oman (e.g., [32]). For the purposes of using the mobile devices, as m-learning has not taken place yet on a large scale on campus, the students naturally use them for the personal and social non-course-related needs more than for course-related learning. YouTube and Facebook are the two most popular social media among Omani adolescents as reported elsewhere (e.g., ITU[46], but meanwhile Twitter and WhatsApp are getting popular. Similar to the finding of [39], Wikipedia and Google Docs are the two most frequently used online applications for the academic purposes. The other tools such as Khan Academy and academia.edu are relatively unknown to most students. LinkedIn, a professional social networking application, is also unpopular among the respondents as in Al-Kindi and Al-Suqri.

Regarding the expectation on the implementation of m-learning, about 96% of the respondents expected it on campus with one year. Among them, over half anticipated m-learning to be part of their learning within six months. These percentages were much higher than the those reported in [47] in a Malaysian sample. However, these differences can be justified as [47] was conducted 10 years ago. Overall, the results reflect students' positive attitude towards m-learning.

Three factors are selected to be independent variables on behavioral intention towards m-learning in the present study based on the literature review: personal, environmental, and technological or system. Computer self-efficacy and the newly explored grit, social network support and facilitation, and perceived ease of use and usefulness of mobile technology were chosen to represent the personal, environmental, and system factor, respectively. The latent dependent variable, behavioral intention, was measured by evaluative attitude and behavior intent. All measurement models demonstrated satisfactory psychometric properties. The factor loadings were solid, and the internal consistency reliability coefficients were as good as in other studies. The factor means are similar to others as well (e.g., [26, 30, 44]).

The hypothesized model with mediation effect through the technology factor appears to have a good fit with the data initially. Nevertheless, when the mediation effects are removed, the prediction model with direct effects only remains almost identical, which implies that the three predictors influence behavioral intention independently. For the direct effects, the system factor in terms of perceived ease of use and usefulness has the largest impact, followed by the personal factor and environmental factors. For the personal factor, skillfulness, passion, and perseverance are all critical elements, indicating the value of grit as a personality trait-level variable in predicting readiness of m-learning. The environmental factor represented by social support and facilitating conditions also contribute to behavioral intention, though less significant than the other two factors. The relatively weak impact of social influence or facilitation was also found in other Arabic samples (e.g., [25, 48]).

Limitation and FutureStudies

This research first contributed to the understanding of the college students' mobile device ownership, utilization profile of the mobile devices, attitudes and expectations towards m-learning, and readiness m-learning. It also contributed to the field with a hypothesized latent model with grit included as part of the equation and had it validated it in a sample. The main limitations were the issues of sample, theoretical model, measurement model, and model testing. First, as the present study employed a convenience sample, its generalizability was limited. Second, the research model was formulated from a very high level due to unavailability of concrete models. Its validity remains to be examined with more empirical studies. Third, although the survey demonstrated solid psychometric properties, it may still lack ethnographical validity in the Omani culture as the items were primarily adopted from studies in other countries. Last, there may be other better fitting models, but they were not explored and tested due to space limitation.

Future studies need to use large and more randomized samples, develop more comprehensive theoretical models with other possibly salient predictor variables, and test other competing models thoroughly. The measurement models can also be improved with better validity and reliability, and then validated with confirmatory factor analysis in preliminary studies.

In addition to supporting theoretical exploration of m-learning readiness through developing structural equation models, the findings from the present study also has several practical implications. First, it clearly shows that the college students are ready for m-learning at the hardware, skill, or attitude level as in SQU (e.g., [49]). But they haven't used mobile technology for their course work at a regular basis yet due to lack of requirement and infrastructural support of m-learning. M-learning can be promising at CAS-Sur if lessons learned from the educationally advanced countries are kept in mind [36]. It should be a natural and welcomed action for the college to integrate m-learning into the existing practices, resulting in a harmonious mixture of traditional, e-learning, and m-learning approaches. Second, the model demonstrates that the seven observed predictors of the personal, environmental and technological factors are all significant variables. This finding provides directions for colleges to help students improve their m-learning readiness such as increasing their computer efficacy by training, boosting their grit through workshop or seminar, providing organizational support, and making m-learning useful and ease to use.

Conclusion

The present study found that the college students in Oman were well familiar with the mobile technology. They had used mobile devices in their daily life, although more for the personal pleasure and social networking needs than for the academic learning purpose. They also expected m-learning to be implemented within a year.

To predict behavioral intention towards m-learning, a latent model with three predictors was hypothesized. The technology or system factor represented by perceived ease use and perceived usefulness contributed the most at 26%. The personal factor in terms of skill and grit also significantly explained about 17% of the variance, whereas the environmental factor of social support and institutional facilitation accounted for the least at 10%, although still significant as well. The three hypotheses on the direct effects of personal, environmental, and environmental factors on behavioral intention of m-learning were supported, whereas the last two hypotheses of the indirect effects of personal and environmental factors through the technology factor were rejected.

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