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The development and validation of a scale measuring mobile phone use in an academic environment

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Abstract: The purpose of this study was to bridge the gap in current research on educational mobile phone use within the framework for the rational analysis of the mobile education (FRAME) model. The paper developed and validated the Mobile Phone Use in Academic Environment Scale (MPUAES) to measure both positive and negative aspects of educational use of mobile phones. The participants were 1887 undergraduate students enrolled in all faculties and grade levels of Middle East Technical University in Ankara, Türkiye. The inclusion criterion for the participation in the study was owning a smartphone. The exploratory and confirmatory factor analyses were run with two different samples. Three factors structure with 18 items were obtained, which were labeled as facilitator, distractor, and connectedness. These three factors explained 63.42% of the total variance. For confirmation of the factor structure, confirmatory factor analysis was performed with the second sample. Cronbach alpha coefficient of each factor ranged between .90 and .74. To conclude, the findings of the study proposed that the scores obtained from the developed scale were valid and reliable in measuring undergraduate students' mobile phone use in an academic environment.

1. INTRODUCTION

The use of mobile phones among college students has increased rapidly in recent years. The "mobility" and "highly customizable" features of the mobile phones enable learners to take control of their own learning and engage in learning activities according to their own needs, interests, and curiosity (Kukulska-Hulme & Shield, 2008). Despite providing such opportunities in learning environments, the opinions on the use of mobile devices in education vary. In other words, there are both proponents and opponents of the educational use of mobile devices in the literature. Correspondingly, Obringer and Coffey (2007) stated "although mobile devices are the central of the students' life in terms of personal and educational purposes, they face inconsistent attitudes among teachers and administrators with regard to use in the school" (p. 43). Bernacki et al. (2020)'s study also showed that mobile technologies can be used to improve learning processes. Additionally, Crompton (2017) refers to supportive role of mobile technologies in terms of

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collaboration However, opponents consider those devices as disruptive and unsuitable tools in an educational context, which causes a challenge for the universities' adoption and use of mobile device in education (Losh, 2014). Regarding this issue, a study conducted by Purba and Setyarini (2020) found that students encountered some concentration problems while using the mobile application in language learning. Some scholars, on the other hand, hold a more holistic perspective and suggest that mobile devices are both a distractor and facilitator in learning environments (Lockhart, 2016). Quaglia and Corso (2014) have a similar opinion and claim that:

> In this era of prolific use and debate regarding the utility, integration, and efficacy of educational technology devices such as tablets and smartphones, one constant that is frequently missing from the purported ideologies and opinionated inferences is the perspective of the learner or user (p.21).

As Quaglia and Corso (2014) highlighted, there was a need to investigate how undergraduate students use their mobile phones for educational purposes in detail. Thus, this study will shed light on the learner perspective on the use of mobile phones in an academic environment. Furthermore, most of the studies of using mobile phones for educational purposes were conducted by using qualitative analyses in the literature (Ford, 2016; Huang, 2016; Dukic & Chiu, 2015; Gikas & Grant, 2013). On the other hand, when the quantitative studies were examined in the field, it was seen that the majority of them were carried out through acceptance models such as TAM and UTAUT (e.g., Han & Yi, 2019; Bryant, 2016; Cheon et al., , 2012; Abu-Al-Aish & Love, 2013; Pan et al., 2013; Iqbal & Qureshi, 2012; Venkatesh et al., 2012; Lowenthal, 2010; Wang et al., 2009). The present study was an attempt to offer a new measurement approach for the assessment of educational mobile phone use. Thus, the purpose of this study was to develop a valid and reliable instrument measuring both positive and negative aspects of mobile phone use of undergraduate students in the academic environment.

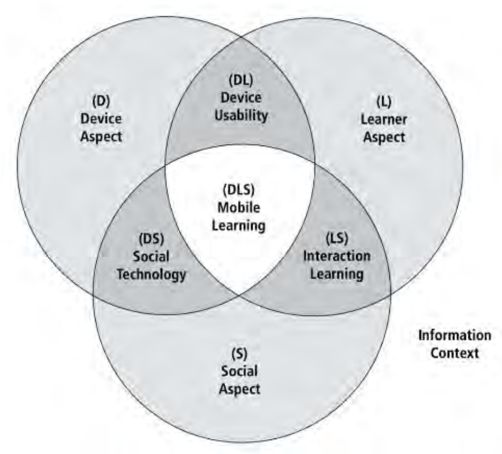
1.1. Mobile Learning

The term "mobile learning" refers to the use of mobile technologies to deliver learning materials to learners (Parsons & Ryu, 2006). Cell phones, smartphones, palmtops, handheld computers, tablet PCs, laptops, and personal media players are typical examples of mobile devices. Since the definition of mobile learning varies among researchers, it is important to clarify how the term is defined in the literature. According to Keegan (2005), mobile learning is "the provision of education and training on smartphones and mobile phones" (p. 3). Similarly, Peters (2007) defined mobile learning as a form of learning supported by mobile technologies. However, these definitions were considered technology-centric by some researchers (Traxler, 2007; Vosloo, 2012). Another definition was provided by Motiwalla (2007), who described mobile learning as individualized learning from anywhere at any time. On the other hand, mobile learning is not regarded as one type of learning in some studies. Indeed, it was defined as learning facilitated by mobile devices (Herrington & Herrington, 2007; Valk et al., 2010).

1.2. The Framework for The Rational Analysis of Mobile Education (FRAME) Model

In order to understand each component of mobile learning, the present study needed an over-arching framework. For this purpose, the FRAME model was chosen, which was developed by Koole (2006) and Koole and Ally (2006). This model was accepted as the first comprehensive theoretical framework for mobile learning. In this model, mobile learning was defined as a process resulting from the convergence of mobile technologies, human learning capacities, and social interaction. It is helpful for educators in terms of planning and designing mobile learning environments (Park, 2011). A Venn diagram was used to represent the FRAME model (Koole, 2009) (see Figure 1).

Figure 1. *The FRAME model.*



The three circles represent three main aspects, namely Device Aspect (D), Learner Aspect (L), and Social Aspect (S). There are also three intersection areas, which are comprised of two different aspects. Device Aspect (D) represents the mobile devices and their technical, physical features, and capabilities. This aspect is important due to behaving as a bridge between the learner and the learning task(s) (Koole, 2009). Learner Aspect (L) refers to the situations and tasks that the student wants or needs to succeed. The learner aspect highlights the learner characteristics that include cognitive ability, memory, prior knowledge, emotions, and possible motivations (Koole, 2009). Social Aspect (S) defines social interaction and cooperation. Device Usability Intersection (DL) includes the elements of both Device Aspect (D) and Learner Aspect (L). This intersection corresponds to the characteristics of mobile devices which influence the learners' psychological comfort and satisfaction while interacting with them. Its functions like a bridge between the characteristics and needs of the learner and the technical features of the mobile device. Social Technology Intersection (DS) includes both Device Aspect (D) and Social Aspect (L). This intersection refers to how mobile devices provide communication and collaboration among multiple learners through multiple systems, and it is mostly based on the philosophy of social constructivism. Learner Aspect (L) and Social Aspect (S) constitute Interaction Learning Intersection (LS). According to Koole (2006), this intersection includes learning and instructional theories, but is largely based on the philosophy of social constructivism. As the primary intersection of the FRAME model, Mobile Learning Process (DLS) contains three elements that belong to Device Aspect (D), Learner Aspect (L), and Social Aspect (S). In an effective mobile learning process, it is expected to provide cognitive environments where learners can appropriately interact with each other, instructors, and course materials (Koole, 2006). In this way, the time for searching information and efforts spend for the evaluation of it are reduced.

2. METHOD

2.1. Instrument Development

The Mobile Phone Use in Academic Environment Scale (MPUAES) was adapted from the Mobile Phone Affinity Scale (MPAS) (Bock et al., 2016). The MPAS scale assessed both negative and positive aspects of mobile phone use in the work environment. Thus, 6-factor of the MPAS was assigned as follows: Connectedness, Productivity, and Empowerment as positive sub-dimensions; Anxious Attachment, and Addiction as negative sub-dimensions; and Continuous Use as a neutral sub-dimension. The present study aimed to develop the Mobile Phone Use in Academic Environment Scale (MPUAES) based on 24 items of the MPAS, which was adapted to the academic environment.

The necessary permissions were taken before starting work on this scale development study. To ensure content validity, the researchers worked with three experts in the field of Computer Education and Instructional Technology Department, one expert in the field of Curriculum and Instruction Department, and one expert in the English Language Department. Besides excluding some words related to the work environment, some words were included to make it suitable for an instructional environment. Furthermore, cognitive interviews with three undergraduate students were conducted before piloting the scale, which was important for detecting possible response errors and finding the reasons for these errors in the survey (Willis, 2004). The students evaluated the items to avoid misunderstanding and hence unintended responses. With the guidance of student comments, some items were revised by adding a more prevalent verb near the less-known words to ease the understanding of participants and make sure that all the items were clear to them. For example, in one of the items, the phrase "keep track of" was used and it was clarified by adding the word "follow" as seen in the following: "My phone helps me keep track of -*follow*- my academic life". Moreover, an operational definition of the concept of "academic life" was given at the beginning of the survey to clarify its meaning and share a common understanding with the students.

2.2. Participants

Data was collected during the fall semester of 2016-2017 and the spring semester of 2017-2018 from all faculties of Middle East Technical University (METU). It was assumed that those familiar with technology would be more willing to fill out the online survey compared to the others who were not quite familiar with it. To ensure common conditions for the completion of the survey, the researchers handed out a hand-delivered questionnaire and the online survey form was not preferred to prevent low internal validity owing to the possibility of a selection threat (selection bias) (Kite & Whitley, 2018). The inclusion criteria for participation in this study were defined as any undergraduate student who was still studying in any department of METU and owned a smartphone. In the demographics section, information regarding gender, current GPA, age, faculty, department, and graduate level was collected.

In the first stage, the factorial structure of the instrument was explored with 240 undergraduate students. The second stage comprised of 1647 participants. In both stages, the data were collected from all faculties and all grade levels of METU (Table 1).

Table 1. *Distribution of the participants in the pilot study and validation study by departments and study year.*

	Pilot study		Validation study	
	Sample1 (n_1 = 240)		Sample2 (n_2 = 1647)	
	f	%	*f*	%
Gender				
Female	140	58.3	832	50.5
Male	100	41.7	815	49.5
Faculty				
Architecture	-	-	98	6.0
Arts & Science	84	35.0	325	19.7
Economics & Administrative Sciences	14	5.8	231	14.0
Education	72	30.0	207	12.6
Engineering	70	29.2	786	47.7
Study Year				
Freshman	70	29.2	447	27.1
Sophomore	70	29.2	468	28.4
Junior	70	29.2	421	25.6
Senior & Senior (+)	70	29.2	311	18.9

2.3. Data Analysis

Initially, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA)were performed through SPSS and AMOS for the development of MPUAES. In addition to EFA and CFA analyses, structural model validation and convergent and divergent construct validity were applied for the validation and confirmation of the factor structure. A pilot study was carried out with 240 undergraduate students. Then, cross-validation analysis was performed for the validation of the three-factor structure of the scale with a sample of 1867 undergraduate students. According to Byrne (2010), this type of analysis offers the advantage of examining the factorial structure of the scale across different samples of the same population. Thus, the sample in the present study was split into two random samples for conducting both EFA and CFA analyses based on the suggestion of Cudeck and Browne (1983).

3. RESULTS

3.1. Findings on Content Validity

The items in the study were generated based on 24 items of the MPAS. The researchers worked with five experts to ensure content validity; three of them were from the Computer Education and Instructional Technology Department; one expert was from the Curriculum and Instruction Department; and one expert was from the English Language Teaching Department. Based on the suggestions of experts, while some words were excluded from the items, some were added to be suitable for an academic environment. Before piloting the study, cognitive interviews were conducted with three undergraduate students. In this way, the possible response errors were detected.

3.2. Findings on Construct Validity

3.2.1. *Exploratory factor analysis*

Before performing the EFA, missing data was examined in the data. Due to the less than five percent on a single variable, it was ignored based on the suggestion of Hair et al. (2010). The sample size for conducting the EFA was checked in two ways. Firstly, 10:1 rule, which means ten cases for each item, or being above 100 cases (Hatcher, 1994) was acceptable to run the EFA. The rules were met for 24 items with 240 cases. Secondly, Kaiser-Meyer-Olkin (KMO) was checked. Since KMO value (.92) was above .60, it was accepted as a great value for sampling adequacy according to Hutcheson and Sofroniou (1999). On the other hand, the data were screened to detect univariate outliers and multivariate outliers. Although some cases were found, as the recommendation of Tabachnick and Fidell (2013), the researcher examined whether the cases were suitably part of the sample and decided not to remove them. As another assumption, univariate normality was checked by Skewness and Kurtosis values, Kolmogorov Smirnov and Shapiro Wilk tests, histograms, and Q-Q plots. The normality assumption was met based on Skewness and Kurtosis values, histogram, and Q-Q plots. Multivariate normality was also checked through Mardia's Test. It was found significant (p = .00), which means the multivariate normality was violated. Lastly, the appropriateness of EFA was checked through a correlation matrix and Barlett's test of sphericity. According to Tabachnick and Fidell (2009), if correlation coefficients are under .30, there is no need to conduct EFA. When the correlation matrix was examined, it was seen that many correlations exceeded this threshold. Moreover, Barlett's test of sphericity was found significant (χ^2 (153) = 2252.40, $p < 0.05$) at the .05 level, which indicates the presence of nonzero correlations. Both the results of the correlation matrix and Barlett's test of sphericity were the indicators of suitability for performing EFA. After all, the preliminary analysis showed that it was appropriate to conduct factor analysis. Since the multivariate normality assumption was not met, Principal Axis Factoring (PAF) was selected as the extraction method (Costello & Osborne, 2005). Moreover, oblique rotation, more specifically direct oblimin, was chosen as a factor rotation method owing to the presence of correlated factors (Preacher & McCallum, 2003).

In order to determine the number of factors, the scree-test and eigenvalues were checked. In the first run of EFA with 24 items, a pattern matrix with 5 factors was observed. With the rule of .30 factor loadings (Fidell, 2006; Hair et. al, 2010), Item 12 and Item 13 were deleted. After removing those 2 items, the EFA was run again. Item 18 and Item 21 were omitted because their communality values were lower than .40 based on the suggestions of Costello and Osborne (2005). Since Item 14 and Item 17 had similar meanings, the lower-loaded one, Item14, was deleted. Although its factor loading was above .30, Item 8 was also deleted since it was loaded on the first factor for which it is not suitable. After omitted the aforementioned items, the EFA was performed with 18 items for the last time. The pattern matrix was screened, and it was observed that all factor loadings were above .40, and there was not any cross-loaded item. The scree pilot indicated the presence of three factors. Eigenvalues were also examined to decide a reliable estimation on the number of factors. According to Tabachnick and Fidell (2013), eigenvalues less than 1 are not important for variance. There were three factors explaining 63.42% of the total variance in the study (see Table 2). Factor 1, 2, and 3 accounted for 41.93, 13.28, and 8.22 of the total variance, respectively.

Table 2. *Pattern coefficient for mobile phone use in academic environment scale*

	Item	Factor 1	2	3	Communality
Facilitator	i16. My phone is necessary for my academic life	**.86**	-.08	-.02	.68
	i1. I feel in control of my academic life when I have my phone with me	**.83**	.07	-.14	.63
	i22. In my academic life, my phone gives me a sense of comfort.	**.79**	-.07	.06	.64
	i17. Without my mobile phone, I feel detached *-out of touch, isolated-* to my academic life.	**.72**	.15	-.18	.50
	i11. Having my phone with me makes it easier to sort out *-resolve, handle-* the critical situations related to my academic life.	**.71**	-.09	.20	.63
	i7. For my academic life, I feel dependent on my phone.	**.69**	.09	.03	.54
	i23. My phone helps me be more organized for my academic life.	**.68**	.01	.20	.64
	i4. When it comes to the academic life, my phone is my personal assistant.	**.61**	-.07	.26	.56
	i6. I feel more comfortable in doing my school work when I have my phone with me.	**.57**	.08	.14	.47
Distractor	i5. When I should be doing the school work, I find myself occupied with my phone.	.02	**.80**	-.03	.64
	i10. I find myself occupied on my phone even when I'm with my classmates or instructors (during the class or studying).	.07	**.73**	.01	.58
	i9. In class or whenever I study, I read/send text messages that are not related to what I am doing.	.04	**.72**	.05	.57
	i3. I would get more school work done if I spent less time on my phone.	-.12	**.66**	.00	.40
	i24. I find myself engaged with my mobile phone for longer than I intended	.09	**.58**	.11	.44
Connectedness	i2. I use my phone to connect with my classmates or instructors	-.12	.05	**.79**	.57
	i1. My phone helps me keep track of *-follow-* my academic life.	.18	.00	**.62**	.53
	i19. My phone helps me stay close to my classmates and instructors.	.16	.14	**.58**	.53
	i20. My phone makes it easy to cancel the arranged plans withclassmates or instructors.	.23	.17	**.53**	.56
	Eigenvalues	7.55	2.40	1.48	
	% of Variance	41.93	13.28	8.22	
	Cronbach's α	.92	.84	.81	

Note. Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization. The items above .30 were signed in bold.

Based on the aforementioned rules, it was concluded that the number of factors to be retained was three. Items 16, 15, 22, 17, 11, 23, 4, and 6 were loaded on Factor 1 labeled as Facilitator; items 5, 10, 9, 3, and 24 were loaded on Factor 2 labeled as Distractor; items 2, 1, 19, and 20 were loaded on Factor 3 labeled as Connectedness.

Kaiser's eigenvalue-greater-than-one rule, namely the Kaiser criterion, is seen as the most approved method in practice (Fabrigar et. al, 1999) and it is also accepted as the most accurate method to reveal the relationships between the items (Büyüköztürk, 2007). Nonetheless, some researchers found this rule problematic and inefficient in determining the number of factors (Ladesma & Pedro, 2007). Therefore, the parallel analysis has been proposed as the best alternative and appropriate method in some studies (Humphreys & Montanelli, 1975; Zwick & Velicer, 1986). Both Kaiser's eigenvalues in the first column and the PA eigenvalues in the third column are seen in Table 3. According to these results, none of the eigenvalues of PA was greater than Kaiser's eigenvalues. This means that there was not a factor obtained by the chance. To conclude, the Kaiser criterion was supported by the results of the parallel analysis upon which the number of factors to be retained was three.

Table 3. *The Results of the Parallel Analysis.*

Factor	Kaiser's eigenvalues	Mean of eigenvalues	PA eigenvalues
1*	7.55	1.51	1.61
2*	2.40	1.41	1.48
3*	1.48	1.33	1.39

**The retained factor according to the results of the parallel analysis.*

3.2.2. *Structural model validation*

A measurement model refers to the linear or nonlinear statistical functions involving the relation between items and constructs to be measured (Yurdugül & Aşkar, 2008). In order to evaluate the proposed measurement model and alternative models, first-order confirmatory factor analysis was performed. As an estimation method, the maximum likelihood (ML) was chosen upon the recommendation of Tabachnick and Fidell (2013) for medium to large sample sizes and plausible assumptions. The data consisted of 240 undergraduate students. In order to investigate factorial validity, five measurement models were used and given in the explanations below.

–Model I indicated 24 items with a unidimensional construct measurement model.

–Model II indicated a six-factor measurement model as proposed in the original scale. These factors were as follows: Connectedness, Productivity, Empowerment, Anxious Attachment, and Continuous Use.

–Model III indicated a three-factor measurement model which was obtained in the present study. Principal Axis Factoring was selected as the extraction method. The model included 18 items, and the factors were as follows: Facilitator, Distractor, and Connectedness. In this model, the three factors were considered to be correlated.

–Model IV indicated a three-factor measurement model which was obtained in the present study, where the latent factors were considered to be uncorrelated.

–Model V (Empirical Measurement Model) indicated a three-factor measurement model which was obtained in the present study; and the factors were correlated. Differently, in order to improve model-fit, some error variances were allowed to covary in this model

The following fit indices were chosen to compare alternative models (Yurdugül, 2007): root mean square error of approximation (RMSEA), goodness of fit index (GFI), comparative fit index (CFI), and non-normed fit index (NNFI). The model-data fits were computed for all the measurement models as depicted in Table 4. The criteria for good-fit-indices are also illustrated in the table.

Table 4. *Good-of-fit indices and comparison of the measurement models.*

		RMSEA	GFI	CFI	NNFI
		<0.08	≥0.90	≥0.90	≥0.90
Model I:	Unidimensional Model	.12	.66	.71	.68
Model II:	Six-Factor Structure	.10	.77	.81	.78
Model III:	3-factor Structure (Correlated)	.10	.82	.87	.85
Model IV:	3-factor Structure (Uncorrelated)	.12	.78	.80	.77
Model V:	3-factor Structure (correlated- covaried)	.06	.92	.96	.95

Note. References*:* Hair et al. (2010). Kline (2011).

Firstly, Model I was built, which was a unidimensional model with 24 items. According to fit indices of the model, Model I showed a poor model fit. This can be interpreted as an indicator that the scale consisting of 24 items did not confirm the one-factor structure model, but it should have more than one sub-construct. Secondly, Model II was based on the six-factor structure model as the original scale, which included 24 items. Although an improvement was observed in the fit indices compared to Model I, it was not sufficient for a good model fit. This was also proof that the scale was not suitable for the six-factor structure model with 24 items. Thirdly, the present study proposed Model III, in which a three-factor structure (correlated) model was obtained from the pilot study. In this model, the number of items dropped from 24 to 18 items. Although the fit indices showed an improvement, they were not in the acceptable range. Similar to Model III, Model IV indicated a three-factor structure model obtained from the present study, but the latent factors were assumed to be uncorrelated. As seen in Table 4, a decline was observed in the good-of-fit indices of the model. Finally, Model V was built, which was a three-factor measurement model with 18 items. The latent factors were correlated; and some error variances which were found highly correlated were allowed to covary in the model. According to the fit indices, Model V was found as the most appropriate among five measurement models. Consequently, it was continued with Model V based on these results in the current study.

3.2.3. *Convergent and discriminant validity*

In the present study, construct validity was also examined by two ways: (1) convergent validity, and (2) discriminant validity. (Yurdugül & Sırakaya, 2013). The present study used three measures to estimate convergent validity of the model. The first rule was that factor loadings should be greater than .050 (Hair et al., 2010). They were between .51 and .82, which met the rule. Secondly, average variance extracted (AVE) was calculated and obtained above .50, which was acceptable according to the rule of thumb greater than .50. Lastly, composite (construct) reliability (CR) was calculated as an indicator of convergent validity. As seen in Table 5, CR values were obtained between .80 and .91, which were acceptable according to the rule of thumb greater .70.

Table 5. *Convergent validity for the measurement model.*

	L Interval (a)	AVE (b)	CR (c)
Facilitator	.61 – .80	.56	.92
Distractor	.51 – .82	.50	.83
Connectedness	.58 – .81	.51	.80

Note. L = Factor Loadings. AVE = Average Variance Extracted. CR = Composite Reliability

For discriminant validity, the correlations among the subscales of the MPUAES and the square root of AVE were used. According to this, the square root of AVE calculated for each dimension must be greater than correlations coefficients between the corresponding sub-dimension and remaining sub-dimensions and must be higher than .50 as well (Fornel & Larcker, 1981). As seen in Table 6, the discriminant validity was ensured.

Table 6. *Discriminant validity for the measurement model.*

	Facilitator (1)	Distractor (2)	Connectedness (3)
Facilitator (1)	**(.75)**		-
Distractor (2)	.43	**(.71)**[b]	-
Connectedness (3)	.71[a]	.55	**(.71)**

Note. The values in parentheses are the square roots of AVE. *a = .7090. b = .7135.*

3.2.4. *Confirmatory factor analysis*

In order to confirm a three-factor structure of MPUAES, CFA was performed with the rest of the data which consisted of 1647 students. Before performing confirmatory factor analysis, the following assumptions were checked, separately: sample size, normality, and absence of outliers (Tabachnick & Fidell, 2013) Firstly, the adequacy of sample size was checked. The thumb rule 1:10 was met with 18 items and 1647 participants (Hair, et al., 2010). Secondly, both univariate and multivariate outliers were screened. For univariate outliers, standardized z-scores and box-plot were checked. 10 cases were detected which exceeded the absolute value of 3.29. Regarding box-plot representations, a few univariate outliers were observed, which were possible for the studies with the large sample size (Pallant, 2007; Tabachnick & Fidell, 2007). As being a multivariate analysis, SEM studies take into consideration multivariate outliers instead of univariate ones. Thus, they were not deleted. For multivariate outliers, Mahalanobis distance (D^2) was calculated for each case. Out of 1647, thirty-seven cases were detected as multivariate outliers with the critical value of 42.312 (df = 18, p = .001). After omitting these cases, the analysis was performed again. It was observed that the results were not substantially affected. That is, 37 cases were determined as possible outliers, which were remained in the data. Thirdly, univariate normality was also checked. Kolmogorov-Smirnov and Shapiro-Wilk test results were found significant, which was a sign of non-normal distribution. However, these tests cannot be considered as only indicators for normality because of being very sensitive to sample size. Skewness and kurtosis values were also checked, which were between -3 and +3. The visual inspection of histogram and Q-Q plots were also observed, in which there was not any evidence for violation of normality. Thus, the univariate normality of the data was assured by skewness and kurtosis values, histogram, and Q-Q plots. As an estimation method, the maximum likelihood (ML) was chosen upon the recommendation of Tabachnick and Fidell (2013) for medium to large sample sizes and plausible assumptions. The following fit indices were selected to assess the goodness-of-fit of the model: Chi-square (χ^2), comparative fit index (CFI), adjusted goodness of fit index (AGFI), goodness of fit index (GFI), non-normed fit index (NNFI), normed fit index (NFI), root mean square error of approximation (RMSEA), root mean square residual (RMR), and standardized root mean square residual (SRMR) (Jöreskog & Sörbom, 1993; Kline, 2011). The model fit indices selected for the current study are presented in Table 7, in which the references for each fit index are also shown.

The second-order CFA resulted a significant chi-square, χ^2 (132, n = 1647) = 1684.21, p = .00, which indicated an unacceptable model. However, according to Tabachnick and Fidel (2013), chi-square is sensitive to sample size. Thus, other fit indices were examined, and the following results were found: CFI = .89, NNFI = .87, GFI = .89, AGFI = .86, RMR = .08, RMSEA = .09, and SRMR = .06. CFI, and NNFI values showed poor model fitting, which should be greater than .95 for a perfect model fit, and at least .90 for a good model fit (Tabachnick & Fidell, 2013; Jöreskog & Sörbom, 1993; Kline, 2011). The same rule was in use for the values of GFI and

AGFI, which also showed poor fitting due to being less than .90 (Hair et al., 2010). In addition, RMSEA value greater than .08 indicates a poor fitting model (Browne & Cudeck, 1993). The values SRMR and RMR were only indicatives of a good fit (Jöreskog & Sörbom, 1993; Kline, 2011). Thus, the researchers examined the error covariances (i.e., modification indices of errors). Eight error covariances (ε4-ε13, ε16-ε17, ε12-ε13, ε7-ε13, ε3-ε5, ε8-ε9, ε1-ε14, and ε1-ε15) were found highly relatively in the program output. As seen in Figure 2, the items related to these error covariances were loaded on the same factors. Before covarying, the relevant items were checked by two experts from the Computer Education and Instructional Technology Department. In the first factor, namely facilitator, item 13 "Without my mobile phone, I feel detached -out of touch, isolated- to my academic life." was related to item 4, item 7, and item 12. When these three items were examined (see Table 9 in Appendix), it was seen that they highlighted the necessity of mobile phones in an academic life. Thus, the experts allowed them to covary in the model. Similarly, under the facilitator factor, the following item pairs, namely item 16 and item 7, were also allowed to covary since both pointed out that it was a great convenience using mobile phones in an academic life. In the distractor factor, one of the error covariances was observed between item 8 and item 9. The experts allowed to covary these errors because both items implied that mobile phones could be a distraction while studying. The other item pairs were item 3 and item 5. They were also allowed to covary since "school work" was the focus in both items. The other two modification errors were under the connectedness factor. Item 1 "My phone helps me keep track of -follow- my academic life" was related to item 14 and item 15. When these two items were checked, "follow academic life" and "keep in touch with classmates and instructors" might be perceived as similar, thus the experts allowed them to covary as well.

Table 7. *The model fit indices used for confirmatory factor analysis.*

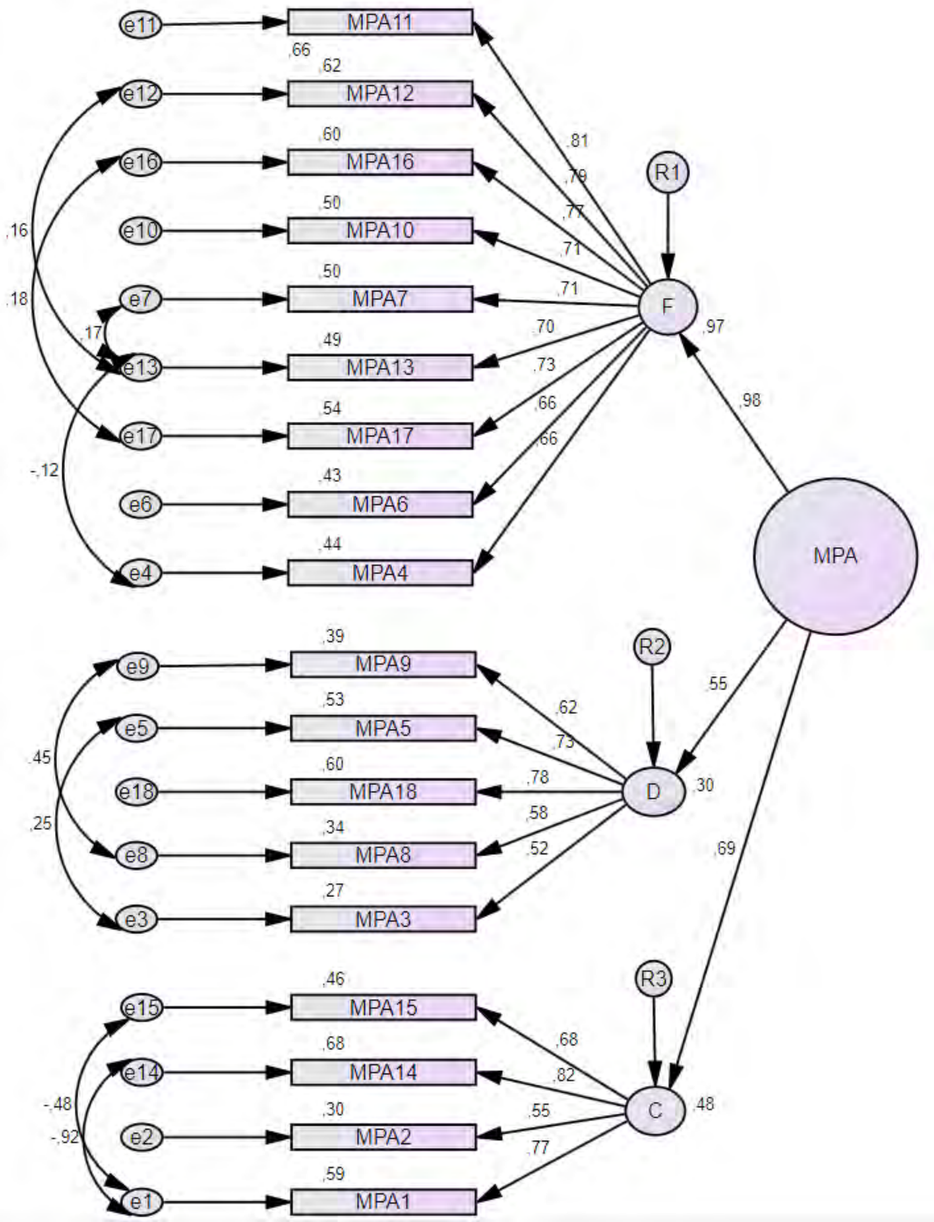
Model Fit Index	Acceptable Fit		Sample Statistics	Decision	References*
	Moderate Fit	Good Fit			
NNFI	.95 - .97	.97 – 1.00	.91	Moderate	a, b, e
CFI	.90 - .95	.95 – 1.00	.92	Moderate	a, b, d, e, f,
GFI	.90 - .95	.95 – 1.00	.92	Moderate	d, f
AGFI	.90 - .95	.95 – 1.00	.90	Moderate	b, e, f,
SRMR	.05 - .08	≤ .05	.06	Moderate	c, d
RMR	.05 - .08	≤ .05	.08	Moderate	c, d
RMSEA	.05 - .08	≤ .05	.07	Moderate	c, f

Note. * References: a = Tabachnick and Fidell (2013). b = Jöreskog and Sörbom (1993). c = Browne and Cudeck (1993). d = Hu and Bentler (1999). e = Kline (2011). f = Hair et al. (2010).

The results revealed a close fit model. The fit indices of the model were as follows: CFI = .92, NNFI = .91, GFI = .92, AGFI = .92, RMR = .08, SRMR = .06 and RMSEA = .07. Chi-square was found significant despite of decreasing the value $\chi 2$ (129, n = 1647) = 1199.574, p = .00. Since chi-square (χ^2) is expected to be significant for large sample sizes, other fit indices should be taken into consideration (Tabachnick & Fidell 2013). All other fit indices, except SRMR value, indicated a good model fit. The SRMR value was found .05, which was an indicator of the perfect fitting model (Hu & Bentler, 1999).

The proposed second-order factor model of MPUAES is shown in Figure 2. The standardized estimates of the second-order factors were .98, .55, and .69. Their standardized factor loadings varied between .66 and .81 for the facilitator factor, varied between .52 and .78 for the distractor factor, and .55 and .82 for connectedness factor. Thus, it can be concluded that all items had a significant contribution to the proposed model since the cut-off point of the standardized estimates of the items was .40 (Stevens, 2002).

Figure 2. *The factor structure of MPUAES with standardized estimates.*



3.3. Findings on Reliability

For internal consistency, Cronbach alpha coefficients were examined for each factor, which was found as .92 for facilitator factor (9 items), .82 for distractor factor (5 items), and .73 (4 items) for connectedness factor. Being greater than .70, these values were acceptable (Nunally, 1978).

3.4. Interpretation of Mobile Phone Use in Academic Environment Scale Scores

The Mobile Phone Use in Academic Environment (MPUAES) comprised of 16 items. A 5-point Likert-type grading scale [Extremely true (5) → Not at all true (1)] was applied on the scale. Three proposed dimension and their items are shown in Table 8: facilitator (9 items), distractor (5 items), and connectedness (4 items). Therefore, possible scores for each dimension range as follows: between 9 and 45 for facilitator; between 5 and 25 for distractor; and between

4 and 20 for connectedness factor. Since a second-order CFA was performed, the total score of the scale was calculated as well. Accordingly, it ranges between 18 to 90 for the whole mobile phone use in an academic environment scale.

Table 8. *The dimensions and items of MPUAES.*

Dimensions	Number of items	Items
Facilitator	9	i11, i2, i16, i10, i17, i7, i13, i6, i4
Distractor	5	i9, i18, i5, i8, i3
Connectedness	4	i15, i14, i12, i1

The evaluation of the MPUAES scores was performed according to both the scores from the subscales and the total score of the scale. This means that besides the dimensions of the scale, the total score related to mobile phone use in an academic environment can be obtained on the scale as well. If the students' scores from the subscales are high, their mobile phone use in terms of relevant dimensions is also high. Likewise, a high total score indicates that students' mobile phone use in an academic environment is high.

4. DISCUSSION and CONCLUSION

The MPUAES was developed based on the 24 items of the MPAS scale with a six-factor structure (Bock et al., 2016). The original scale was developed for a work environment, which was adapted to the academic environment in this study. First, a pilot study was carried out with 240 students and the EFA was run several times to diagnose the problematic items. As a result of this process, six problematic items were omitted and a three-factor structure with 18 items was obtained. The number of factors was decided based on scree plot, Kaiser's eigenvalues, and the parallel analysis. Then, the validation of the three-factor structure of the scale was performed with 1647 students. To sum up, the MPUAES proposed a three-factor structure with 18 items: facilitator (9 items), distractor (5 items), and connectedness (4 items) (see Table 9 in Appendix). Cronbach alpha coefficients were examined for each factor, which was found as .92, .82, and .73, respectively. Being greater than .70, these values were acceptable (Nunally, 1978).

According to the results of factor analysis, three factors were obtained, which were labeled as facilitator, distractor, and connectedness, upon FRAME model developed by Koole (2006). According to this model, mobile learning consists of three aspects: (1) Device, (2) Learner, and (3) Social. That is, besides the technical specifications of the mobile devices, social and personal dimensions of learning should be considered in the context of mobile learning. Furthermore, in the FRAME model, each aspect intersected with the other one and formed three intersections, which are device usability (device and learner aspect), social technology (social and device aspect), and interaction learning (learner and social aspect). The intersections of these three aspects lead to the ideal mobile learning. In the MPUAES, the three factors, namely facilitator, distractor, and connectedness, covered the aforementioned three main aspects and three intersections of the FRAME model. More specifically, the factors were assigned as follows: technical features of smartphones as device aspect; facilitator and distractor sub-dimensions as learner aspect; and connectedness sub-dimension as the social aspect. For instance, item 2 "I use my phone to connect with my classmates or instructors" corresponds to the social aspect of the FRAME model. Apart from the association of the items with the main aspects of the model, they were also related to the intersections. For instance, item 23 loaded on facilitator factor "My phone helps me more organized for my academic life" consisted of both device and learner aspect, so it corresponds to the intersection of device usability, as well. Similarly, item 9 under distractor factor "In class or whenever I study, I read/send text messages that are not related to what I am doing" was associated with all three intersections due to including functionality of the device, social relationship, and learner characteristics. Although all items were associated with all aspects and intersections of the model in some way, the learner aspect was essential for the MPUAE scale because of focusing on students' experiences with their mobile phones in the academic environment such as prior knowledge, skills, emotions, and motivations, etc. Thus, it can be concluded that MPUAES was primarily based on the learner aspect of the FRAME model, and also as the characteristics of the FRAME model, the scale was a convergence of mobile technologies, learner characteristics, and social interaction.

To conclude, the results of the study indicated that the scores obtained from the developed scale MPUAES were valid and reliable in assessing undergraduate students' mobile phone use in an academic environment. The study had some significant implications which should be considered by researchers interested in mobile technologies usage in higher education. The present study provided a comprehensive perspective on undergraduate students' educational mobile phone use by considering both positive and negative aspects. Apart from the technology acceptance models, the current study offered a new measurement approach for the assessment of educational mobile phone use. Yet, the inclusion of only one university was one of the limitations of this study. To enhance generalizability and external validity (Merriam & Tisdell, 2015), the study might further be conducted with different universities from different regions of Turkey. Moreover, the criterion-based validity could not be checked due to the absence of an educational mobile phone use scale that can be used as a criterion. Thus, this can be further analyzed in the future studies. Lastly, this study focused especially on the learner aspect. Further studies might focus on other aspects of the FRAME model.

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Declaration of Conflicting Interests and Ethics

The authors declare no conflict of interest. This research study complies with research publishing ethics. The scientific and legal responsibility for manuscripts published in IJATE belongs to the author(s). **Ethics Committee Number**: 2017-FEN-003, İnsan Araştırmaları Etik Kurulu (İAEK)

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Nehir YASAN AK: Investigation, Resources, Visualization, Software, Formal Analysis, and Writing - original draft. **Soner YILDIRIM**: Investigation, Methodology, Supervision, and Validation.

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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 Distributed Learning*, *14*(5). https://doi.org/10.19173/irrodl.v14i5.1631

Bernacki, M.L., Greene, J.A., & Crompton, H. (2020). Mobile technology, learning, and achievement: Advances in understanding and measuring the role of mobile technology in education. *Contemporary Educational Psychology*, *60*, 101827. https://doi.org/10.1016/j.cedpsych.2019.101827

Bock, B.C., Lantini, R., Thind, H., Walaska, K., Rosen, R.K., Fava, J.L., ... & Scot Sheldon, L. A. (2016). The mobile phone affinity scale: enhancement and refinement. *JMIR mHealth and uHealth, 4*(4). https://doi.org/10.2196/mhealth.6705

Bryant, E.C., (2016). *Graduate student perceptions of multi-modal tablet use in academic environments* [Doctoral dissertation, University of South Florida]. The USF Libraries. https://core.ac.uk/download/pdf/154477153.pdf

Browne, M.W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J.S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Sage. https://psycnet.apa.org/record/1993-97481-000

Büyüköztürk, Ş. (2007). *Sosyal bilimler için veri analizi el kitabı (*7. Baskı). [Data analysis handbook for social sciences]. Pegem Akademi Yayınları.

Byrne, B.M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). Routledge. https://doi.org/10.4324/9780203805534

Cheon, J., Lee, S., Crooks, S.M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers and Education*, *59*(3), 1054–1064. http://doi.org/10.1016/j.compedu.2012.04.015

Costello, A.B., & Osborne, J.W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment Research and Evaluation, 10*(7). http://pareonline.net/pdf/v10n7.pdf

Crompton, H. (2017), Moving toward a mobile learning landscape: presenting a mlearning integration framework. *Interactive Technology and Smart Education*, *14*(2), 97-109. https://doi.org/10.1108/ITSE-02-2017-0018

Cudeck, R., & Browne, M.W. (1983). Cross-validation of covariance structures. *Multivariate Behavioral Research, 18*(2), 147-167. https://doi.org/10.1207/s15327906mbr1802_2

Fabrigar, L.R., Wegener, D.T., MacCallum, R.C., & Strahan, E.J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological methods*, *4*(3), 272-299. https://doi.apa.org/doi/10.1037/1082-989X.4.3.272

Field. A. (2009). *Discovering statistics using by SPSS* (3rd ed.). London: Sage Publication. https://uk.sagepub.com/en-gb/eur/discovering-statistics-using-sas/book234095

Ford, J.R. (2016). *Learners' Perspectives on How Mobile Computing Devices Usage Interacts with Their Learning* (Order No. 10168369). Available from ProQuest Dissertations & Theses Global. (1846531179). https://www.proquest.com/dissertations-theses/learners-perspectives-on-how-mobile-computing/docview/1846531179/se-2

Fornell, C., & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gikas J., & Grant, M.M. (2013). Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media. *The Internet and Higher Education. 19,* 18-26. https://doi.org/10.1016/j.iheduc.2013.06.002

Hair, J.F., Anderson, R.E., Tatham, R.L., & Black, W.C. (2010). *Multivariate Data Analysis* (7th ed.). Prentice Hall, Inc. https://doi.org/10.1016/j.iheduc.2013.06.002

Han, S., & Yi, Y.J. (2019). How does the smartphone usage of college students affect academic performance? *Journal of Computer Assisted Learning*, *35*(1), 13-22. https://doi.org/10.1111/jcal.12306

Hatcher, L. (1994). *A step-by-step approach to using the SAS® system for factor analysis and structural equation modeling.* Cary, NC, USA: SAS Institute, Inc. https://www.sas.com/storefront/aux/en/spsxsfactor/61314_excerpt.pdf

Herrington, A., & Herrington, J. (2007, November). *Authentic mobile learning in higher education* [Paper presentation]. Australian Association for Research in Education Conference, Fremantle, Western Australia. https://www.aare.edu.au/07pap/her07131.pdf

Hu, L.H. & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-15. https://doi.org/10.1080/10705519909540118

Huang, R.T., Jang, S.J., Machtmes, K., & Deggs, D. (2012). Investigating the roles of perceived playfulness, resistance to change and self-management of learning in mobile English learning outcome. *British Journal of Educational Technology*, *43*(6), 1004-1015. https://doi.org/10.1111/j.1467-8535.2011.01239.x

Humphreys, L.G. & Montanelli, R.G. (1975). An investigation of the parallel analysis criterion for determining the number of common factors. *Multivariate Behavioral Research*, *10*, 193-206. https://doi.org/10.1207/s15327906mbr1002_5

Hutcheson, G., & Sofroniou, N. (1999). *The multivariate social scientist: Introductory statistics using generalized linear models.* Sage. https://uk.sagepub.com/en-gb/eur/the-multivariate-social-scientist/book205684

Iqbal, S., & Qureshi, I.A. (2012). M-learning adoption: A perspective from a developing country. *The International Review of Research in Open and Distributed Learning*, *13*(3), 147-164. https://doi.org/10.19173/irrodl.v13i3.1152

Jöreskog, K.G., & Sörbom, D. (1993). *LISREL 8: Structural equation modeling with the SIMPLIS command language.* Chicago: Scientific Software International. https://psycnet.apa.org/record/1993-97878-000

Keegan, D. (2005, October). *The incorporation of mobile learning into mainstream education and training* [Paper presentation]. 4th World Conference on mLearning, Cape Town, South Africa. Google Scholar

Kite, M.E., & Whitley, B.E. (2018). *Principles of Research in Behavioral Science* (4th ed.). Routledge. https://doi.org/10.4324/9781315450087

Kline, R.B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). New York: The Guilford Press. ftp://158.208.129.61/suzuki/PP_SEM_3e.pdf

Koole, M.L. (2006). *The framework for the rational analysis of mobile education (frame) model: an evaluation of mobile devices for distance education* (Doctoral dissertation). Athabasca University, Athabasca, AB, Canada, 2006. http://hdl.handle.net/2149/543

Koole, M., & Ally, M. (2006, April). *Framework for the rational analysis of mobile education (FRAME) model: Revising the ABCs of educational practices* [Paper presentation]. International Conference on Networking, International Conference on Systems and International Conference on Mobile Communications and Learning Technologies, Morne, Mauritius. https://doi.org/10.1109/ICNICONSMCL.2006.103

Koole, M.L. (2009). A model for framing mobile learning. In M. Ally (Ed.), *Mobile learning: Transforming the delivery of education and training* (pp. 25-47). Athabasca University Press. https://www.aupress.ca/app/uploads/120155_99Z_Mohamed_Ally_2009-MobileLearning.pdf#page=45

Kukulska-Hulme, A., & Shield, L. (2008). An overview of mobile assisted language learning: From content delivery to supported collaboration and interaction. *ReCALL, 20*(3), 271-289. https://doi.org/10.1017/S0958344008000335

Lockhart, K.S. (2016). *A comparison of the attitudes of administrators and teachers on cell phone use as an educational tool* (Order No. 10075104). Available from ProQuest Central; ProQuest Dissertations & Theses Global. (1777350856). https://www.proquest.com/dissertations-theses/comparison-attitudes-administrators-teachers-on/docview/1777350856/se-2

Losh, E. (2014). *The war on learning: Gaining ground in the digital university*. USA: MIT Press. https://mitpress.mit.edu/books/war-learning

Lowenthal, J.N. (2010). Using mobile learning: Determinates impacting behavioral intention. *The American Journal of Distance Education*, *24*(4), 195-206. https://doi.org/10.1080/08923647.2010.519947

Merriam, S.B., & Tisdell, E.J. (2015). *Qualitative research: A guide to design and implementation*. John Wiley & Sons. GoogleScholar

Motiwalla, L. (2007). Mobile learning: A framework and evaluation. *Computers and Education, 49*(3). 581-596. https://doi.org/10.1016/j.compedu.2005.10.011

Nunnally, J.C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill. Google Scholar

Obringer. J. & Coffey. K. (2007). Cell phones in American high schools: A national survey. *The Journal of Technology Studies, 33*(1), 41-47. https://eric.ed.gov/?id=EJ847358

Purba, M., & Setyarini, S. (2020, October). Mobile Learning through WhatsApp: EFL Students' Perceptions. *12th International Conference on Education Technology and Computers* (pp. 27-32). https://doi.org/10.1145/3436756.3437016

Park, Y. (2011). A pedagogical framework for mobile learning: Categorizing educational applications of mobile technologies into four types. *The International Review of Research in Open and Distributed Learning*, *12*(2), 78-102. https://doi.org/10.19173/irrodl.v12i2.791

Parsons, D., & Ryu, H. (2006, April). *A framework for assessing the quality of mobile learning* [Paper presentation]. 11th International Conference for Process Improvement, Research and Education, Southampton, UK. Google Scholar

Peters, K. (2007). M-Learning: Positioning educators for a mobile, connected future. *International Review of Research in Open and Distance Learning, 8*(2). https://doi.org/10.19173/irrodl.v8i2.350

Preacher, K.J., & MacCallum, R.C. (2003). Repairing Tom Swift's electric factor analysis machine. *Understanding statistics: Statistical Issues in Psychology, Education, and the Social Sciences, 2*(1), 13-43. https://doi.org/10.1207/S15328031US0201_02

Quaglia, R., & Corso, M. (2014). *Student voice: The instrument of change*. Corwin: A Sage Company: Thousand Oaks, CA. https://us.corwin.com/en-us/nam/student-voice/book243538

Stevens, J.P. (2002). *Applied multivariate statistics for the social sciences* (4th ed.). Hillsdale, NJ: Erlbaum. https://psycnet.apa.org/record/1992-98099-000

Tabachnick, B.G., & Fidell, L.S. (2013). *Using multivariate statistics.* Allyn and Bacon. https://www.pearsonhighered.com/assets/preface/0/1/3/4/0134790545.pdf

Traxler, J. (2007). Defining, discussing and evaluating mobile learning: The moving finger writes and having writ... *The International Review in Open and Distance Learning, 8*[2], 1–13. Google Scholar

Wang, Y.S., Wu, M.C., & Wang, H.Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology*, *40*(1), 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x

Willis, G.B. (2004). *Cognitive interviewing: A tool for improving questionnaire design*. Sage Publications. https://www.jstor.org/stable/27641121

Valk, J.H., Rashid, A.T., & Elder, L. (2010). Using mobile phones to improve educational outcomes: An analysis of evidence from Asia. *The International Review of Research in Open and Distributed Learning*, *11*(1), 117-140. https://doi.org/10.19173/irrodl.v11i1.794

Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Vosloo, S. (2012). *Mobile learning and policies: Key issues to consider*. Paris, France: UNESCO. http://unesdoc.unesco.org/images/ 0021/002176/217638E.pdf

Yurdugül, H. (2007). The Effects of Different Correlation Types on Goodness-of-Fit Indices in First Order and Second Order Factor Analysis for Multiple Choice Test Data. *İlköğretim Online*, *6*(1), 154-179. https://ilkogretim-online.org/?mno=121223

Yurdugül, H., & Aşkar, P. (2008). An investigation of the factorial structures of pupils' attitude towards technology (PATT): A Turkish sample. *Elementary Education Online*, *7*(2), 288–309. http://ilkogretim-online.org/fulltext/218-1596636637.pdf?1612882858

Yurdugül, H., & Sırakaya, D.A. (2013). The scale of online learning readiness: A study of validity and reliability. *Education and Science*, *38*(169), 391-406. https://hdl.handle.net/20.500.12513/1731

APPENDIX

Table 9. *The last version of the mobile phone use in academic environment scale (MPUAES).*

Please use the 1-5 scale provided ("Not at all true" to "Extremely true") to rate how TRUE for YOU the following statements are.	1 – Not at all true	2 – A little true	3 – Somewhat true	4 – Very true	5 – Extremely true
1. My phone helps me keep track of *-follow-* my academic life.	☐	☐	☐	☐	☐
2. I use my phone to connect with my classmates or instructors	☐	☐	☐	☐	☐
3. I would get more school work done if I spent less time on my phone.	☐	☐	☐	☐	☐
4. When it comes to the academic life, my phone is my personal assistant.	☐	☐	☐	☐	☐
5. When I should be doing the school work, I find myself occupied with my phone.	☐	☐	☐	☐	☐
6. I feel more comfortable in doing my school work when I have my phone with me.	☐	☐	☐	☐	☐
7. For my academic life, I feel dependent on my phone.	☐	☐	☐	☐	☐
8. In class or whenever I study, I read/send text messages that are not related what I am doing.	☐	☐	☐	☐	☐
9. I find myself occupied on my phone even when I'm with my classmates or instructors (during the class or studying).	☐	☐	☐	☐	☐
10. Having my phone with me makes it easier to sort out *–resolve, handle-* the critical situations related to my academic life.	☐	☐	☐	☐	☐
11. I feel in control of my academic life when I have my phone with me.	☐	☐	☐	☐	☐
12. My phone is necessary for my academic life.	☐	☐	☐	☐	☐
13. Without my mobile phone, I feel detached *-out of touch, isolated-* to my academic life.	☐	☐	☐	☐	☐
14. My phone helps me stay close to my classmates and instructors.	☐	☐	☐	☐	☐
15. My phone makes it easy to cancel the arranged plans with classmates or instructors.	☐	☐	☐	☐	☐
16. In my academic life, my phone gives me a sense of comfort.	☐	☐	☐	☐	☐
17. My phone helps me be more organized for my academic life.	☐	☐	☐	☐	☐
18. I find myself engaged with my mobile phone for longer than I intended.	☐	☐	☐	☐	☐