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The effects of a mobile pre-learning system with surface learning approach on academic achievement and mobile learning attitude

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ABSTRACT

Background/purpose – The main purpose of this study is to examine the effects of the mobile pre-learning system developed according to the surface learning approach on academic achievement and mobile learning attitudes.

Materials/methods – The research was conducted with 135 university students and a 12-week pretest–posttest unequaled control group quasi-experimental research method. Prepared in line with the content of an Instructional Technologies course, 12 educational videos varying from 3 to 6 minutes, and designed according to the surface learning approach, were issued to the experimental group's students via the mobile pre-learning system 1 day prior to the relevant lesson, and the data obtained were then analyzed.

Results – As a result of the research, it was determined that the mobile pre-learning system developed according to the surface learning approach had a significant effect on the participant students' academic achievement and mobile learning attitudes.

Conclusion – It was observed that the mobile pre-learning system developed according to the surface learning approach had a close to medium-level effect on the satisfaction and motivation factors of the participant students' mobile learning attitudes. However, it was determined that it had no significant effect on the impact and usefulness factors of learning. In addition, it was concluded that the mobile pre-learning system based on the surface learning approach had a significant effect on the participant students' academic achievement.

Keywords – Surface learning, mobile pre-learning system, academic achievement, mobile learning attitude, distance learning, learning approaches, SOLO taxonomy.

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1. INTRODUCTION

The impact of mobile devices on daily life is increasing each day. According to the "Digital in 2020" report (Kemp, 2020), there are 5 billion, 190 million individual mobile device users worldwide. This rate corresponds to 67% of the world's population. The average daily time people spend using the Internet worldwide is 6 hours and 43 minutes. Turkey, meanwhile, is 12th in terms of countries that spend the most time using the Internet, with 7 hours and 29 minutes. In this context, the interaction times of Turkey's young population with mobile technologies is considered to be quite high. Generally, the largest demographic of mobile device users are those aged between 18 and 29 years old, which predominantly covers the college education age (Crompton & Burke, 2018). For this reason, mobile technologies have become one of the most popular topics in educational technology research. More and more studies are being conducted on the effective and efficient use of mobile technologies in the process of education.

When the literature is examined, it can be seen that mobile technologies at the doctoral level are mostly employed in language education (Alioon, 2016; Bakay, 2017; Gülcü, 2015; Okumuş-Dağdeler, 2018; Özer, 2017; Tanır, 2018; Zengin 2018). Especially in the research of blended learning, it has been observed that traditional technologies are used the most, and that there has been limited research on the effectiveness of mobile technologies in this area.

Recently, it has been observed that numerous studies have been conducted on the "inverted" or "flipped classroom" model, which is a sub-dimension of blended learning. Although this model is a sub-formation of blended learning, it is not a model considered equal to blended learning (Staker & Horn, 2012). In essence, the flipped classroom model argues that the theoretical part of a course should be completed outside of the class, and that the more important part, which includes the application dimension, should be conducted as in-class activities. Accordingly, students generally study the theoretical part of the lesson individually, and prior to attending the in-class lesson, by way of utilizing technological equipment and Internet-based learning objects. As a result, the students are able to perform the application dimension of the lesson under the practical guidance of the teacher. Accordingly, it is surmised that more permanent and deeper learning can be achieved, and that students are better able to manage their learning processes according to the constructivist model.

However, when the literature is examined, it appears that many studies have not found any meaningful effect in terms of academic achievement based on the transformed classroom model (Butzler, 2014; Howell, 2013; Overmyer, 2014; Yavuz, 2016).

Although the flipped classroom model contains some contradictions within itself, it is observed that the process is carried out without taking any precautions on these points. The first of these contradictions is that the theoretical load of the course is left entirely on the students. Osguthorpe and Graham (2003) emphasized that to obtain maximum benefit from blended learning, the beneficial aspects of traditional learning and online learning should be combined in a balanced way. While the model states that the problems experienced in the theoretical dimension can be best overcome during in-class activities, the fact that the theoretical dimension, which can be problematic for students anyway, and may contain somewhat different content, can necessitate additional explanatory information regarding the theory learning; which is an issue that is largely ignored.

Another contradiction is in the content of the theoretical knowledge. According to the model, it is expected that the theoretical part of the learning is completed prior to attending the lesson, which is then developed further by applying it during the lesson. However, the deep learning process must be started in order to fully understand the theoretical part of the course, establish relationships with past learning, and to understand the functions of concepts as well as their connections with other concepts. When criticism of Talan's (2018) flipped classroom model are examined, the length of videos and the excessive workload of students due to their taking on greater responsibility for their learning draw attention. However, in order to be successful in any online learning environment, a high degree of self-management is a definite requirement (Shapley, 2000).

Deep learning approaches aim at desired learning products such as higher academic achievement, skill development, and meaningful learning (Gibbs, 1994; Newstead, 1992; Pandey & Zimitat, 2007; Zimitat & McAlpine, 2003). However, in order for deep learning to take place, learners must possess high self-regulation skills, be intrinsically motivated, and be sufficiently open to benefit perception (Biggs, 1987; Haggis, 2003; Marton, 1983). In addition to this, results-oriented, low-motivation studies have also been included in the field of surface learning. In the online learning environment, learners decide whether or not a learning activity will be subject to surface learning or deep learning, and undoubtedly many factors are impactful in such a decision. According to Alt and Boniel-Nissim (2018), individuals who have been in contact with social media and instant communication tools for a long time are more likely to adopt the surface learning approach. Considering the time spent by Turkey's university-age population using such digital tools, this factor becomes much more significant. However, in many technology-based research studies on education, it can be seen that models that adopt the deep learning approach are preferred, and that their content is often prepared according to deep learning as well.

In order to effectively direct students towards deep learning, it is necessary for teachers to suitably structure the lessons and to predetermine the tasks and activities that the students are required to attempt, whilst also providing feedback and guidance services that help to encourage the development of deep learning (Hattie, 1998, 2002). For this, the teacher must be at the center of the lesson in order to actively manage the whole teaching-learning process. In environments without the provision of teacher guidance and control, it is a very natural result that students with a focus on surface learning respond to deep content with surface learning. Involving students in the learning process by posing high-level analytical questions is an important factor in the whole deep learning process. From this perspective, where students start to ask various questions, this helps to improve their understanding of the content, and helps to create more independent students who can self-organize and self-direct their own individual learning according to their own needs (Dillon, 1988; Wong, 1985). Therefore, whether asked by the teacher or the students, the use of questions in the learning environment encourages more in-depth processing of the learning material (Offir et al., 2008).

This is especially pertinent in the synchronous lesson process of distance education, where it is naturally much more difficult to create a deep learning environment. In the model known as "transactional distance," in which the importance of interaction in distance education and its effect on learning time was examined by Moore (1993), a potentially increasing distance between the teacher and students during the lesson was defined. The model assumes that operational distance is a pedagogical phenomenon, that is, geographical distance causes a gap in students' understanding and perception of teaching that is not generally seen in the conventional face-to-face classroom teaching environment. According to Moore, physical distance in distance education can turn into a psychological gap, which can the lead to misunderstandings in the behaviors of both teachers and students. This distance refers not to physical distance, but the psychological-communicative distance that can impair communication and thereby understanding. Furthermore, according to Moore, transactional distance is affected by two variables, namely, dialogue or verbal interaction, and also the adaptation of this to distance learning. As the level of dialogue increases, the transactional distance will decrease; resulting in increased learning effectiveness. However, today's online synchronous classes do not provide that many opportunities to create the optimal level of dialogue due to students being largely unprepared for their lessons, with short course periods, and increasing levels of content density, etc.

Generally speaking, the concepts of deep and surface approaches to learning emerged in the study of Marton and Saljö (1976), who discovered in their text reading study that different students may have different intentions when approaching the same task. They noticed that while some students wanted to understand the meaning of the text, others focused primarily on the questions that might be related to the text. In this process, the students who had the intension of making sense of their reading tried to associate existing information with previous information, to structure the ideas as an understandable whole, and to critically evaluate the information and results presented in the text. However, students who undertook the same task as a challenge of text memorization relied more upon the rote learning strategy. Consequently, whilst the first group characterized the deep learning approach, the second group embodied the surface learning approach.

Haggis (2003) described and exemplified the characteristics of surface and deep learning approaches. Accordingly, deep learners associate topics and ideas with previous knowledge and experiences. This competence is also accepted as a constructivist learning activity, referring to the idea that content and skills should be understood within the framework of the student's prior knowledge (Alt, 2014). In this sense, the learner is intrinsically interested in the content and strives to understand the person trying to do the explaining (Trigwell et al., 2005). Students often favor referring back to their own experiences and prior knowledge in order to understand learning materials more clearly, as opposed to surface learning which is centered on memorization and provides interactions with a limited amount of data (Price, 2014).

Unlike deep learners, surface learners do not provide detailed information on facts or interact with content or ideas. Their intention is to passively accept content ideas and to only process information on a simplistic level. They focus only on what is required for the assessment, rely upon rote learning, see tasks as tiresome, are only extrinsically motivated to learn, and often aim to repeat the material (Haggis, 2003).

Learning approaches are related to the perceived demands of the learning environment and not entirely dependent on personal characteristics (Biggs & Tang, 2007; Nijhuis et al., 2005). Therefore, the goals of the learning environment can influence which approach students will adopt. At the same time, how students perceive certain factors in the learning environment, and also their preliminary knowledge of the subject matter, can also affect their approach (Gijbels et al., 2014).

Biggs and Collis (1982) demonstrated the effect of learning goals on the learning approach with the "Structure of Observed Learning Outcomes (SOLO)" taxonomy, which shows continuity from surface to deep learning. The SOLO taxonomy is structured with five main hierarchical levels that reflect the learning quality of a particular section or task. SOLO Taxonomy is derived from examining results in various academic content areas and can be used to evaluate the quality of student responses. Since its introduction in the early 1980s, it has been widely used in educational practices and research (Smith et al., 2005). Biggs and Collis (1982) suggested that as the depth of student learning increases, the work that students produce as evidence of what they have learned exhibit similar stages of increasing structural complexity. In their research on student results, Biggs and Collis (1982) found that as the amount of detail in the responses of students increased, the responses firstly differed in quantitative terms, and as the detail became integrated into a structural model, the answers also differed in qualitative terms. SOLO taxonomy structured by Biggs and Collis (1982) is presented in detail in Figure 1.

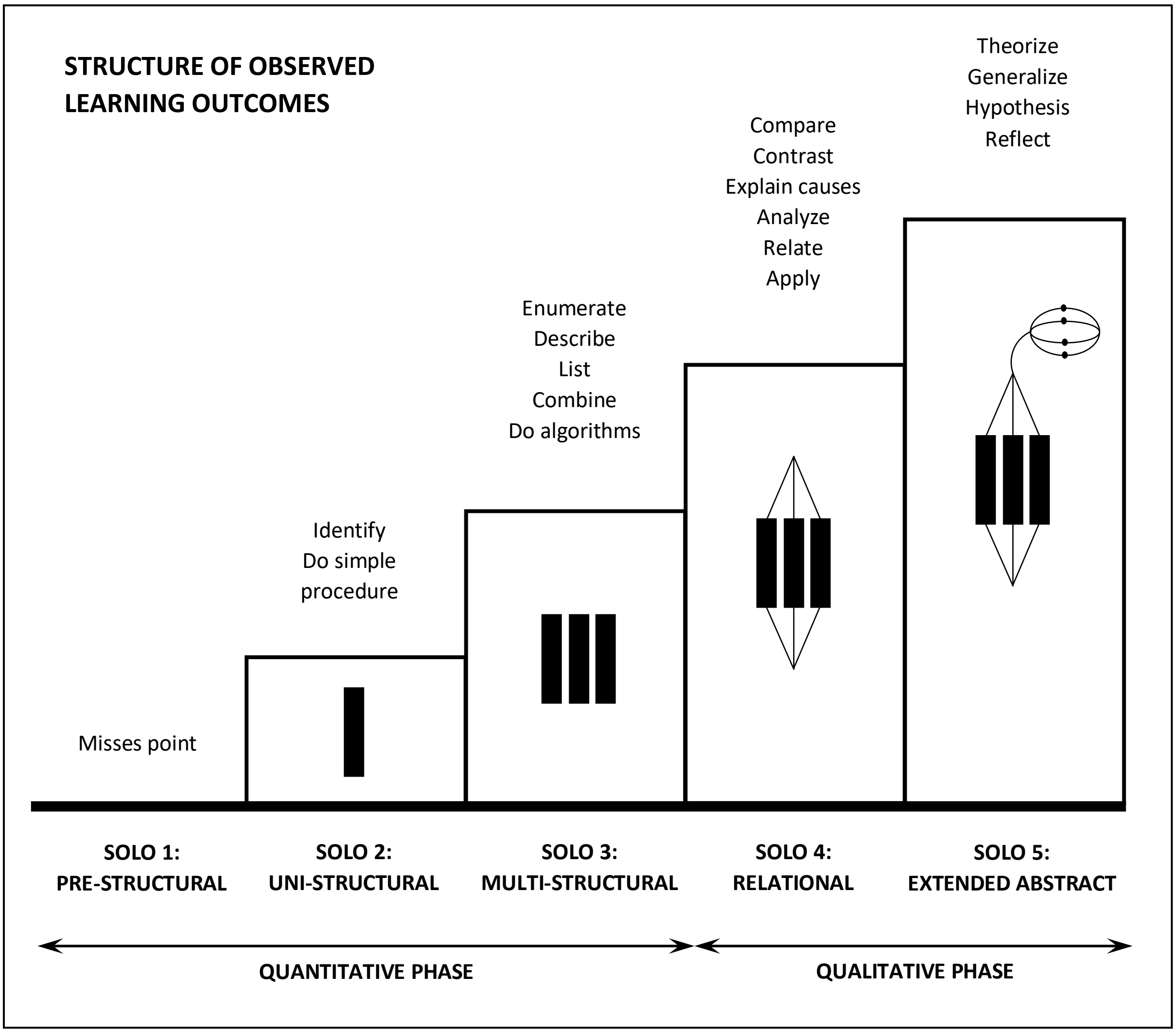

Figure 1. Graphical representation of SOLO taxonomy levels (Biggs, 1999)

Accordingly, the first pre-structural level represents a response that is unrelated or simply misses the point. The next two uni-structural and multi-structured levels correspond to surface learning, whilst the last two levels represent deep learning. Each learning outcome represents any of these five levels. In this sense, in order to be able to move to a higher level, learning outcomes at lower levels must be met. This requires the execution of processes in the field of surface learning first in order for deep learning to take place. Instead of creating all learning processes with a deep approach, in some cases, the surface approach or perhaps better, a combination of both the deep and surface approaches should be employed in the aim to teach effectively (Dinsmore & Alexander, 2012).

The current research study aims to provide students with the basic content only within the scope of surface learning prior to the lesson, and then to provide more opportunities for deep learning processes during the lesson. In this context, the effects of the mobile pre-learning system, which was developed according to the surface learning approach of SOLO taxonomy, on academic achievement and mobile learning attitudes were examined.

Videos for the mobile pre-learning system were developed; the longest of which was 6 minutes. The self-information about the subject to be covered by the students in synchronous education was presented to the students via the mobile system one day prior to their in-class lesson. It was predicted that students who come to the lesson with basic knowledge about the content in line with the surface learning approach will be able to deepen their existing prior surface knowledge by making more effective use of the course content, thus increasing their academic achievement and attitudes towards mobile learning. As such, the following two research hypotheses were formed for this study:

- H_1: Mobile pre-learning system positively affects academic success.
- H_2: Mobile pre-learning system positively affects mobile learning attitudes.

2. METHODOLOGY

In this study, to examine the effects of the mobile pre-learning system developed according to surface learning principles on academic achievement and mobile learning attitudes, a pretest–posttest was conducted with a quasi-experimental design with unequaled control groups as the study groups could not be determined according to unbiased assignment (Büyüköztürk, 2001; Yıldırım & Şimşek, 1999). The symbolic expression of the research pattern is presented in Table 1.

Table 1. Research Design

Group	*Before procedure*	*Experimental procedure*	*After procedure*
G1	$O_{1.1}$	X	$O_{1.2}$
	A_1		A_2
G2	$O_{2.1}$		$O_{2.2}$

G1: Experimental Group
G2: Control Group
X: Independent variable (experimental procedure)
$O_{1.1}$, $O_{2.1}$: Pre-experimental measurement (pretest)
$O_{1.2}$, $O_{2.2}$: Post-experimental measurement (posttest)
A_1: Attitude analysis prior to experimental procedure
A_2: Attitude analysis following experimental procedure

2.1. Study group

The study group of the research consisted of 114 female and 21 male students (total 135 students) from nine different teaching fields at Gazi University's Education Faculty in Ankara, Turkey. Groups were assigned to existing classes in a mixed way. Whilst the Experimental Group consisted of 90 students, the Control Group had 45. The simple random method (Büyüköztürk, 2001) was used in the creation of the groups. All of the participating students were informed about the research during the first week of the course, and their consent to participate in the study was obtained. The characteristics of the study group and their distribution within the groups were as follows:

Table 2. Working Group Characteristics

Department	*Group*	*Number*	*%*	*Total*
English Language Teaching	Experimental	23	25.5	44
	Control	21	46.6	
Primary Education	Experimental	16	17.7	25
	Control	9	20.0	
Elementary Mathematics Education	Experimental	18	20.0	22
	Control	4	8.8	
Mathematics Teaching	Experimental	6	6.6	6
	Control	-	-	
Turkish Language Teaching	Experimental	14	15.5	16
	Control	2	4.4	
Turkish Language and Literature Teaching	Experimental	5	5.0	9
	Control	4	8.8	
French Language Teaching	Experimental	2	2.2	6
	Control	4	8.8	
Chemistry Teaching	Experimental	5	5.5	6
	Control	1	2.2	
Preschool Teaching	Experimental	1	1.1	1
	Control	-	-	

2.2. Instruments

As the data collection tools of the study, an "Achievement Test" was developed by the researcher to analyze the change in the participants' academic achievement, whilst the "Attitude Scale towards Mobile Learning" developed by Demir and Akpınar (2016) was used to analyze the change in the participants' mobile learning attitude.

Achievement Test: The applied test consisted of 48 questions, and was developed by the researcher. The initial version of the test had 62 questions and was designed according to the table of specifications created by considering the course outcomes. After expert evaluation, the test was reduced to 58 questions and was then pre-applied to 180 students. Following validity and reliability analysis, the number of questions was further reduced to its final form with 48 items. The item discrimination index of the test ranged from .31 to .49, whereas the item difficulty index ranged from .28 to .79, and the KR-20 internal consistency coefficient was determined as being .79.

Attitude Scale on Mobile Learning: The scale consists of 45 items in total and with four factors: Satisfaction, Impact on learning, Motivation, and Usefulness. Item loads of the scale were found to range between .82 and .40, whilst the Cronbach Alpha reliability coefficient was determined as being .950.

2.3. Mobile pre-learning system

Within the scope of the research, 12 videos that varied between 3 and 6 minutes' duration were developed based on the surface learning approach for the Instructional Technologies course. The scenarios of the videos were examined and evaluated by three field experts. These videos aimed to provide the students with a basic level of information about each lesson and content as a guide to the important points of the lesson, and was shown to the students 1 day prior to the relevant class. However, the responsibility of learning prior to the lesson was not left to the student. The educational videos were delivered to the students through the mobile pre-learning system developed by the researcher; the aim being that the students would interact with their mobile phones. This system recorded the amount of time that the students spent on the video content and the number of times that they watched each of the videos. Likewise, the pre- and post-executions of the Achievement Test and Attitude Scale on Mobile Learning, as the data collection tools of the research, were also conducted through the mobile pre-learning system.

2.4. Data analysis

The data obtained within the scope of the research were analyzed using IBM's SPSS program according to Shapiro-Wilk, paired sample *t*-test, Wilcoxon Signed Ranks Test, and ANCOVA.

3. RESULTS

In order to analyze the effects of an experimental procedure on academic achievement, a success test was applied to the study group before and after the experimental procedure. Whether or not the data obtained showed normal distribution was tested with the Shapiro-Wilk analysis.

Table 3. Academic achievement data normality analysis (Shapiro-Wilk)

Test	Group	Statistic	df	Sig.
Pretest	Experimental	.977	90	.119
	Control	.979	45	.596
Posttest	Experimental	.989	90	.666
	Control	.954	45	.071

$p < .05$ significant

According to the results of the analysis, the pretest data from the Experimental Group were determined as $W(90) = .98$, $p = .119$; the pretest data from the Control Group as $W(45) = .98$, $p = .596$; the posttest data from the Experimental Group as $W(90) = .99$, $p = .666$; and the posttest data from the Control Group as $W(45) = .95$, $p = .071$. It was concluded that all of the obtained data showed normal distribution. At the same time, it was observed that the Skewness and Kurtosis data of all datasets were distributed within the limits of -1.5 and 1.5, as recommended by Tabachnick and Fidell (2013).

ANCOVA analysis was utilized in order to examine the academic achievement data depending on the pretest data. Outside of the normal distribution prior to the analysis, the assumptions of analysis which are independent observation, normality, homogeneity, homogeneity of regression slopes, and linearity were reviewed, and all of the assumptions were found to be met.

Table 4. Academic achievement: unadjusted & covariate adjusted descriptive statistic

	Before Procedure			After Procedure (Unadjusted)		After Procedure (Adjusted)	
	n	Mean	SEmean	Mean	SEmean	Mean	SEmean
Experimental Group	90	52.11	0.98	64.77	1.08	64.28	0.87
Control Group	45	49.40	1.22	60.14	1.12	61.12	1.24

According to the explanatory statistics data, the posttest average of the Experimental Group and the Control Group were rearranged for the ANCOVA analysis according to the pretest averages. Before the analysis, the homogeneity of variances was analyzed with Levene's Test, from which it was seen that variances of $F(1, 133) = 1.202$, $p = .275$ fulfilled the condition of homogeneity.

Table 5. Analysis of change in academic achievement after experimental procedure (ANCOVA)

Source	*SS*	*df*	*MS*	*F*	*p*	η^2
Pretest	3139.537	1	3139.537	45.925	.000	.26
Experimental Procedure	293.720	1	293.720	4.297	**.040**	.03
Error	12473.194	132	83.713			

a. $R^2 = .295$ (Adjusted a. $R^2 = .285$), $p < .05$ significant

According to the results of the analysis, it was concluded that the experimental procedure had a significant effect on the academic achievement of the students in favor of the Experimental Group $F(1, 132) = 4.30$, $p = .040$, $\eta^2 = .03$. The effect size was determined as $\eta^2 = .03$, and according to this, it was observed that the effect size remained at a low level.

The effects of the experimental procedure on the participants' mobile learning attitudes were analyzed with the dependent sample *t*-test. Whether or not the obtained data showed normal distribution was then tested according to Shapiro-Wilk analysis.

Table 6. Normality analysis of attitude data on mobile learning (Shapiro-Wilk)

Test	Statistic	*df*	Sig.
Pre-attitude	.988	90	.565
Post-attitude	.984	90	.338

According to the results of the analysis, the pre-attitude data were $W(90) = .99$, $p = .565$ and the post-attitude data were $W(90) = .98$, $p = .338$. It was concluded that all of the data showed normal distribution. At the same time, it was seen that the Skewness and Kurtosis data of all the datasets were distributed within the boundaries of -1 to 1 (Hair et al., 2013).

Table 7. Attitude analysis towards mobile learning (Paired Samples *t*-Test)

	M	*SD*	*df*	*t*	*p*	Cohen's *d*
Pre-attitude	149.26	15.234	89	-3.591	.001	.38
Post-attitude	154.79	13.255				

$p < .05$ significant

According to the results of the analysis, it was concluded that the experimental procedure had a significant effect on the mobile learning attitude of the participant students as seen from the data, $t(89) = 3.59$, $p = .001$. For this analysis, the effect size was determined as Cohen's $d = .38$ and it was observed that the effect size exceeded the small effect limit ($d = .20$) of Cohen (1988) and remained below the medium effect ($d = .50$) limit.

Each of the sub-dimensions of Satisfaction, Impact on learning, Motivation, and Usefulness in the Attitude Scale on Mobile Learning were analyzed separately and the changes in each of the sub-dimensions examined.

Table 8. Satisfaction sub-dimension data normality analysis (Shapiro-Wilk)

Test	Statistic	*df*	Sig.
Pre-attitude	.982	90	.260
Post-attitude	.983	90	.285

According to the results of the analysis, the pre-attitude data for the Satisfaction sub-dimension was determined as $W(90) = .982$, $p = .260$ and the final attitude data as $W(90) = .983$, $p = .285$. It was concluded that all of the data showed a normal distribution. At the same time, it was seen that the Skewness and Kurtosis data of all the datasets were distributed within the boundaries of -1 to 1 (Hair et al., 2013).

Table 9. Satisfaction sub-dimension analysis (Paired Samples *t*-Test)

	M	*SD*	*df*	*t*	*p*	Cohen's *d*
Pre-attitude	64.97	9.286	89	-4.270	.000	.45
Post-attitude	69.13	8.916				

$p < .05$ significant

According to the results of the analysis, it was concluded that the experimental procedure had a significant effect on the Satisfaction sub-dimension of the Attitude Scale on Mobile Learning of the students, as seen from the data, $t(89) = 4.270$, $p = .000$. For this analysis, the effect size was determined as Cohen's $d = .45$, and it was observed that the effect size exceeded the small effect limit ($d = .20$) of Cohen (1988) and was very close to the medium effect ($d = .50$) limit.

As a result of the normality analysis of the impact on learning dimension, the pre-attitude data showed normal distribution with $W(90) = .984$, $p = .348$, but the final attitude data was not found to be normally distributed as seen in the data $W(90) = .967$, $p = .023$. For this reason, Wilcoxon Signed Ranks Test, one of the nonparametric analysis methods, was used in the analysis.

Table 10. Impact on learning sub-dimension analysis (Wilcoxon Signed Ranks Test)

		n	*M*	*t*	*Z*	*p*
Pre – Post attitude	Negative	42[a]	41.94	1761.50	-.819[b]	.413
	Positive	46[b]	46.84	2154.50		

$p < .05$ significant

According to the results of the analysis, it was concluded that the experimental procedure did not have a significant effect impact on the Learning sub-dimension of the mobile learning attitudes of the participant students, as seen from the data $t = 1761.50$, $p = .413$, $z = -.819$.

Table 11. Motivation sub-dimension data normality analysis (Shapiro-Wilk)

Test	Statistic	*df*	Sig.
Pre-attitude	.977	90	.103
Post-attitude	.982	90	.257

According to the analysis results, the pre-attitude data were determined as $W(90) = .977$, $p = .103$ and the final attitude data as $W(90) = .982$, $p = .257$ for the Motivation sub-dimension. It was concluded that the data showed normal distribution. At the same time, it was observed that the Skewness and Kurtosis data of the datasets were distributed within the boundaries of -1 to 1 (Hair et al., 2013).

Table 12. Motivation sub-dimension analysis (paired samples *t*-Test)

	M	*SD*	*df*	*t*	*p*	Cohen's *d*
Pre-attitude	21.64	3.896	89	-3.827	.000	.40
Post-attitude	23.61	4.456				

$p < .05$ significant

According to the results of the analysis, it was concluded that the experimental procedure had a significant effect on the Motivation sub-dimension of the mobile learning attitudes of the students, as seen from the data $t(89) = 3.827$, $p = .000$. For this analysis, the effect size was determined as Cohen's $d = .40$ and it was seen that the effect size exceeded the small effect limit ($d = .20$) of Cohen (1988) and approached the medium effect ($d = 0.50$) limit.

Table 13. Usefulness sub-dimension data normality analysis (Shapiro-Wilk)

Test	Statistic	*df*	Sig.
Pre-attitude	.982	90	.244
Post-attitude	.985	90	.372

According to the analysis results, the pre-attitude data were determined as $W(90) = .982$, $p = .244$ and the final attitude data as $W(90) = .985$, $p = .372$ for the Usefulness sub-dimension. It was concluded that the data showed normal distribution. At the same time, it was observed that the Skewness and Kurtosis data of the datasets were distributed within the boundaries of -1 to 1 (Hair et al., 2013).

Table 14. Usefulness sub-dimension analysis (Paired Samples *t*-Test)

	M	*SD*	*df*	*t*	*p*	Cohen's *d*
Pre-attitude	21.64	3.429	89	-0.281	.779	.02
Post-attitude	21.78	3.957				

$p < .05$ significant

According to the results of the analysis, it was concluded that the experimental procedure had a significant effect on the Usefulness sub-dimension of the mobile learning attitudes of students, as seen from the data $t(89) = .281$, $p = .779$. The effect size for this analysis was determined as Cohen's $d = .02$.

4. DISCUSSION, CONCLUSION AND SUGGESTIONS

As a result of the analysis conducted, the significant effect of the experimental procedure on the participant students' academic achievement confirmed the H_1 hypothesis. In this context, it can be said that students who came to the lesson with basic prior knowledge based on the educational videos (having been designed according to the principles of surface learning) engaged in activities that deepened this prior knowledge during the course, and which resulted in a significant difference being noted in the students' academic achievement. However, considering the technology usage habits of today's higher education students, their tendency to interact mostly with concise content, and the transformation resulting from high-level usage of social media tools in their technology consumption habits, it may be said that educational technology applications have not fully kept up with the general advances in technology.

The idea that the traditional approach and the detailed, deep and intensive teaching content will result in the most effective learning, which leaves all of the learning responsibilities to the students and without close guidance and support, has not resulted in the desired effect. High levels of self-regulation skills and motivation, along with many other factors, have led to the current situation; however, the most important problem today is the slow transformation in educational approaches. In particular, understanding education based on measurement has resulted in learning as become an instrument rather than a goal. Especially in recent years, approaches aimed at ensuring that all students are able to study at higher standards have resulted in the establishment of a system where we equate high standards with high test scores (Smith & Colby, 2007). Such systems appear to limit the probability of students going beyond surface learning thinking (Kohn, 2000). For this reason, students only focus on educational content that will enable them to overcome the measurement activity in the best way possible. This approach leads to a lack of deep learning, with the information learned often losing all significance in the eyes of the learner immediately following the measurement activity, and an increasing decrease in the total effect of education on the individual.

The subject of the search in educational technology has changed from technological tools to the role of technology in providing the best education. According to Brenton (2009), e-learning tools and trends were updated quickly, progressing as major projects that aimed to revolutionize education at the turn of the 21st century. There is now a pressing effort to reuse learning materials, and to launch distance education programs that create largescale, contextual, individual learning environments. Nowadays, the focus is on what constitutes good teaching, regardless of the materials used, and therefore, how to best provide successful learning is the dominant question being asked.

Although educators may attempt to identify the most appropriate surface or deep learning approach to teaching (Boulton-Lewis et al., 2001), it is known that various personal factors are highly influential in this selection (Gijbels et al., 2014). Although all educational materials are designed according to the principles of deep learning, the planned approach is not always reflected in the students themselves as learners.

Deep learning is built upon surface learning, and it is the students, who are directly responsible for deep learning, who face the most difficulty in constructing this. The high number of escapes experienced in the latter minutes of long training videos and the duration of the most watched videos on popular video applications substantiate this finding. In the Turkish context, this may be as a result of the constructivist approach not having been incorporated into the national education system, and that today's students (and parents) still demand teacher-centered, measurement-oriented education, and shy away from [students] taking on the responsibility of learning acquisition. For deep learning to be actually realized, it is important to have teacher-student interaction accompanying the learning process (Offir et al., 2008). In their study with 40 graduate students using the SOLO taxonomy, Boulton-Lewis et al. (1996) concluded that 80% of students stayed within the multi-structured level; meaning the field of superficial learning, and needed teacher guidance in order to enter the relational or abstract level, i.e., deep learning. Accordingly, keeping deep learning in the learning approach in situations without teacher guidance does not create the desired result.

The current study aimed to build a foundation for deep learning, which is considered the ideal situation, by appropriately preparing learners for their course content, and by making lesson processes more effective so as to teach in a form more suited to the habits of the target learners' profile.

Undoubtedly, it is not an easy task to simply "direct" learners towards the deep learning approach. Although differentiating the technology usage habits of today's younger generation presents perhaps the biggest challenge, it is necessary to reconstruct measurement-oriented education models that encourage students to carry out surface learning; and to change the educational target from measured activities to learning motivation. In addition, rather than focusing on simply learning course content, students should be provided with strategies and guidance on how to learn, and methods developed for students to best manage their own learning without the need for overt teacher guidance.

Furthermore, as seen in the current study, the fact that the experimental procedure significantly affected the participant students' mobile learning attitudes also confirmed the H_2 hypothesis. As a result of this research, the Satisfaction and Motivation sub-dimensions of the Attitude Scale on Mobile Learning showed a difference in an effect size close to the middle level, and was determined as having not affected the students' learning in terms of the Impact on learning and Usefulness sub-dimensions. It is notably striking that although it was shown to affect academic achievement, the Impact on learning sub-dimension attitude was not found to have changed. However, it may be said that the changes in the dimensions of Motivation and Satisfaction increased the students' interest in the lesson, and that this helped to contribute to their academic success. Changes in the students' satisfaction and motivation showed that they interacted with the educational video content without having become bored. When the minute-based video viewing rates of the mobile learning system were examined, it was seen that the video escapes started only after 90% of the videos had been watched, which was a positive reflection of having purposefully kept the video contents short in duration. Considering that the last 10% of the videos were mostly covering the closing sentences and credits, it may be said that the academic content itself reached almost 100% of the students.

In conclusion, learning approaches play a key role in achieving educational goals. At this point, developing tools that can analyze which learning approaches students use the most will undoubtedly create an important subject for future academic research. Learning approaches should be handled in a more planned manner in the attainment and measurement processes, and strategies should be developed by educators specifically for this whilst developing educational goals.

Notes This study was produced from the first author's doctoral thesis, prepared under the supervision of the second author.

DECLARATIONS

Author Contributions The authors contributed equally to the study.

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Ethical Approval In order to conduct the study, written permission was obtained from the Ethics Committee of Gazi University (Decision number: 2021-288). All participants took part in the study voluntarily, and their identities have been kept confidential.

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