

Profiling University Students' Technology Acceptance Through UTAUT

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ABSTRACT

Several studies have been conducted on e-learning acceptance among university students. Most of these studies examined various factors and individual characteristics as predictors of actual use and behavioral intention for e-learning systems. However, latent profile analysis was used in the present study, adopting a person-centered approach. Accordingly, the study's primary purpose was to define LMS acceptance profiles by grouping university students based on gender according to four main UTAUT predictor variables. The secondary purpose was to examine the extent to which LMS acceptance profiles had a relationship with the students' online self-regulation and engagement in online learning environments. The participants in the study were 397 students from a state university in Turkey who continued their distance education. Student Engagements Scale, Online Self-regulation Questionnaire, and Learning Management System Acceptance Scale were used to collect data. The obtained data were analyzed using latent profile analysis. The results obtained in the study revealed that there were three different student profiles: "very low LMS acceptance", "low LMS acceptance", and "high LMS acceptance". According to another result, it was seen that low online self-regulation and engagement had a relationship with a student profile with very low LMS acceptance and that high online self-regulation and engagement had a relationship with a student profile with high LMS acceptance. Based on the findings, various implications were made about increasing students' LMS acceptance.

Keywords: *Technology acceptance, UTAUT, latent profile analysis, multi-group profile analysis.*

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INTRODUCTION

Following the COVID-19 pandemic, the importance of online learning has increased worldwide. In this process, many educational institutions and universities used Learning Management Systems (LMS) to facilitate online learning (Raza et al., 2021). LMSs are important web-based technologies used to support learning and teaching processes in educational settings (Zararavasan & Ashrafi, 2019). Alias and Zainuddin (2005) define LMS as a web-based technology developed to design, implement and evaluate a learning process. LMS allows easy access to information regardless of time and location, interaction of students with learning content, communication between student-student and student-teacher, and active participation of students in the online learning environment (Iqbal, 2011). Many examples of LMS are used in higher education institutions, and the most famous examples include Google Classroom, Edmodo, Moodle, Blackboard, and WebCT.

E-learning or online learning usually provides more convenience and flexibility (Sadaghiani, 2011). In addition, e-learning environments increase profits by reducing costs for educational institutions (Saade & Bahli, 2005). However, the success of e-learning systems ultimately depends on the successful functioning of online learning courses and the degree of student acceptance (Almaiah & Alismaiel, 2019). For this reason, the growing literature focuses on technology acceptance related to online learning and examines the factors affecting technology acceptance (Al-Adwan et al., 2021). One of the most widely used theoretical frameworks to measure user acceptance in these studies was the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). UTAUT focuses on users' intention to use and use behavior regarding information technology (Venkatesh et al., 2003).

LMSs offer numerous opportunities, but efficient utilization is necessary to benefit from these opportunities. Otherwise, this may cause discontent among stakeholders and rejection of the LMS (Park et al., 2016). University students, one of these stakeholders, have different backgrounds regarding the use of technology, and their acceptance of e-learning environment systems may, therefore, differ. For this reason, identifying the characteristics of similar student groups using the e-learning environment can increase the system's efficiency by providing necessary information to guide future initiatives (Garone et al., 2019). Thus, educational institutions will work to effectively implement the system and invest in this technology (Raza et al., 2021). In this respect, by profiling their LMS acceptance characteristics based on the UTAUT model, the present study tried to explain how students who used LMS (ALMS) in the distance education process at a university in Turkey accepted the system. In addition, the relationships of these profiles with students' online self-regulation and engagement in online learning environments were examined.

LITERATUR REVIEW

UTAUT

The UTAUT model was used as the theoretical basis of this study. The UTAUT model is an integrated model developed by Venkatesh et al. (2003) and is based on a combination of eight leading theoretical models of information technology acceptance. These models are the combined TAM and TPB (C-TAM-TPB), the motivational model (MM), the model of PC utilization (MPCU), social cognitive theory (SCT), the innovation diffusion theory (IDT), the theory of planned behavior (TPB), the technology acceptance model (TAM), the theory of reasoned action (TRA), and the innovation diffusion theory (IDT). Venkatesh et al. (2003) found that the combined model predicted a variance of 69% in users' behavioral intention and pointed out that this was higher than previous models, which predicted only 17% to 53%. Based on the previous literature, Chao (2019) stated that the most effective model for technology acceptance is UTAUT. Therefore, this model is an effective tool for investigating whether students accepted the LMS. The UTAUT model has four basic structures that predict behavioral intention and actual use (Venkatesh et al., 2003). These are performance expectancy, effort expectancy, social influence, and facilitating conditions. Furthermore, in this model, age, gender, experience, and voluntariness are critical moderator variables.

Performance expectancy, one of the main determinants of UTAUT, is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). In other words, it is an individual's belief in the potential of an intended technology to improve performance while doing his/her job. When evaluated in terms of students, performance expectancy is regarded as the student's belief about whether the system is effective for studying (Decman, 2015). Effort expectancy is "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). Users or students accept faster use of a new technology that is user-friendly and guides learning (Sun et al., 2008). Social influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). In assessing acceptance of the LMS, social influence is the degree to which a student's social environment influences his/her LMS use intention (Raza et al., 2021). Lastly, facilitating conditions are "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003). Regarding the e-learning environment, facilitating conditions are related to the prerequisites of the expected technical and organizational infrastructure for using the LMS (Decman, 2015).

Many studies have been carried out on UTAUT. Singh and Thomas (2020) examined the effect of mobile user typology on adopting mobile learning in higher education. The study based on the UTAUT model found that there were four types of users (eclectic users, Internet users, basic users and offline entertainment users) and that these user types had a relationship with gender, age, program level and program type. In another study, Kurt and Tingöy (2017), using the UTAUT model, evaluated technology acceptance and use in virtual learning environments in higher education. As a result of the study, the United Kingdom students demonstrated higher use intention and frequency than those in Turkey. They also stated that the students in the UK adapted to these systems more quickly; the researchers attributed the reason for this to the fact that the students in the UK could more easily access the Internet and digital technologies than those in Turkey.

Online Self-Regulation

Self-regulation is a concept at the center of social cognitive theory. It specifically refers to the processes by which individuals set and maintain their goals (Lord et al., 2010). Self-regulation in education is defined as the spontaneous feelings, thoughts and actions that an individual carries out and plans periodically to achieve his/her personal goals (Zimmerman, 2000). To be considered 'self-regulatory', a student should be metacognitively involved in his/her learning process and be active and motivated (Zimmerman, 1986; Hong & O'Neil, 2001). It was reported that skilful, self-regulated students have higher intrinsic goal orientation and academic self-efficacy. In addition, students more capable of self-regulation can better adjust their learning processes (Pintrich, 2004; Zimmerman & Schunk, 2011). Zimmerman (2000) defined self-regulation as a cyclical process that includes three stages: goal setting, task strategies and self-evaluation.

Just as students' behavioral intentions to use new technologies are an important component that affects their success in e-learning environments, self-regulated learning is a potential factor affecting students' success in online learning environments (Broadbent & Fuller-Tyszkiewicz, 2018; Cho & Shen, 2013). There are no classrooms in the online learning environment as in traditional face-to-face education. Besides that, several supporting factors, such as familiar learning situations, group pressure and social factors, disappear in the e-learning environment (Zvacek, 1991). In addition, there is usually no direct communication between the student and the teacher, or the instructor may not be involved in the process (Sharma et al., 2007). As a result, e-learning environments require students to be more involved in learning processes and to have more self-regulation skills (Artino & Ioannou, 2008). Lee and Choi (2011) found that lack of online self-regulation skills is a major cause of college dropout rates.

Studies revealed that students' self-regulation skills had a relationship with technology acceptance. However, these studies generally looked at predictive relationships with technology acceptance. For example, Zhou et al. (2021) used the TAM model and found that students were more likely to use online cognitive learning strategies when they had more behavioral intention to use e-learning systems. Using the UTAUT model, Chen and Hwang (2019) found that in terms of metacognition and motivation, self-regulation had a direct relationship with performance expectancy, effort expectancy and social influence. The researchers also stated that motivation, effort expectancy, and performance expectancy directly and significantly affected university students' intention to use online courses (Chen & Hwang, 2019). Liaw and Huang (2013) reported that perceived satisfaction, perceived usefulness, and interactive learning environments predicted perceived self-regulation in the online learning environment. Similar studies found that self-regulation was related to intention to use ICT (Roca & Gagné, 2008; Lee et al., 2015).

Student Engagement in Online Learning Environment

There are various definitions for student engagement in the literature. However, most researchers agree that engagement generally reflects the time and effort students spend in academic activities related to learning outcomes (Kuh, 2009; Richardson & Newby, 2006; Skinner & Belmont, 1993). Student engagement is often conceptualized as a multidimensional structure comprising behavioral, cognitive, and emotional domains (Fredricks et al., 2004). Behavioral engagement includes students' engagement in academic, social and extracurricular activities that contribute to their academic success (Fredricks et al., 2004). Cognitive engagement involves students' willingness to make the necessary effort to understand complex ideas and master challenging skills (Skinner & Belmont, 1993). Finally, emotional engagement is

defined as emotional reactions (positive/negative) such as students' boredom, anxiety and interest in learning environments (Fredricks et al., 2004).

LMS can benefit students when it supports their engagement in and out of the classroom (Francom et al., 2021). Student engagement tools that support self-assessment and student-centered activities are essential for student success (Chandra & Fisher, 2009). LMS use particularly increased students' engagement in higher education (Barua et al., 2018; Jordan & Duckett, 2018). In addition, the design elements of LMS can affect students' engagement in LMS. According to Zanjani et al. (2017), LMS design elements that affect user engagement refer to a user-friendly structure, avoiding too many tools and connections, privacy, anonymous posting support and more customizable student-centered tools. The design elements of an LMS can affect students' engagement in e-learning environments and their acceptance of e-learning environments. When the literature is examined, it is seen that studies are showing the relationships between engagement in LMS and acceptance of LMS. Ustun et al. (2021) carried out one of these studies. In their study, in which Moodle was used as the LMS, it was revealed that the perceived usefulness and perceived ease of use, which are the components of the technology acceptance model, were influential factors in increasing university students' engagement. In another study, Cigdem and Ozturk (2016) pointed out that an increase in the multimedia features and interaction of the LMS system might lead to higher perceived usefulness and ease of use among students. Both factors would increase students' perceived satisfaction and thus increase their engagement.

Gender

In the UTAUT model, gender significantly moderates the effect of UTAUT-independent variables on behavioral intention to use technology (Venkatesh et al., 2003). Similarly, many studies show that gender has a moderate effect on LMS use intention and its actual use (Al-Sheri et al., 2020; Wang et al., 2009; Al-Azawei, 2019).

Although different results were obtained in studies, many researchers revealed gender differences in the behavior of individual technology use. For instance, Padilla-Meléndez et al. (2013) examined technology acceptance and its use in terms of gender differences using the TAM model in their study conducted with university students in a blended learning environment. In the study, it was found that the intention of the male participants to use the LMS system was higher than that of female participants. No significant difference was found with respect to gender regarding perceived usefulness and perceived ease of use. In another study, Ong and Lai (2006) investigated gender differences in online learning acceptance. As a result of the study, it was seen that the male participants' perceived usefulness was more important and more distinct than that of the female participants in determining the behavioral intention to use e-learning. According to another result, the male participants' scores regarding computer self-efficacy, perceived usefulness, perceived ease of use and e-learning intention to use were higher than those of the female participants. Cheng and Yuen (2020) compared secondary school students' e-learning system usage behaviors with respect to their different social backgrounds. They found that the girls were more likely to continue using LMS than the boys. Wang et al. (2009) stated in their study that the effect of social influence on the intention to use mobile learning was significant for men yet insignificant for women. Lastly, Al-Azawei (2019) showed that perceived ease of use predicted perceived technology usefulness for both males and females. They also stated that perceived LMS usefulness directly affected behavioral intention and attitudes towards LMS use and that there was no gender divide, though.

Present Study

In the literature, UTAUT and TAM models are common in studies conducted on university students' acceptance and use of e-learning. These studies generally examined various factors and individual characteristics as predictors of actual use and behavioral intention for e-learning systems. However, these studies did not focus on users' e-learning acceptance profiles. In this respect, researchers argue that designing the LMS considering user acceptance profiles will affect the adoption of e-learning and that it is, therefore, an area that needs to be investigated. Moreover, studies which associated LMS acceptance with students' online self-regulation and engagement mostly looked for predictive relationships through structural equation modelling and regression analysis. However, the relationship of these variables, considered a distal outcome in the present study, with the acceptance profiles of the students was analyzed

using the Latent Profile Analysis. In addition, studies examining the effect of gender on LMS acceptance generally considered gender as a moderating variable. In this respect, this study adopted a person-centered approach and aimed to define LMS acceptance profiles by grouping university students based on gender according to four main UTAUT predictor variables. The study also examined the extent to which LMS use profiles had a relationship with the students' online self-regulation and engagement in online learning environments. In line with this, the research questions directed in this study were as follows:

- What profiles can be identified for university students' LMS acceptance based on gender, and what characterizes them?
- To what extent does profile membership have a relationship with university students' online self-regulation and engagement in online learning environments (Distal Outcomes) based on gender?

METHOD

A person-centered approach was used in this study. The person-centered approach is based on the assumption that a known human population may contain many unobserved subgroups with different variant configurations (Wang & Hanges, 2011). The major advantage of the person-centered approach is that it identifies complex relationships between personality traits and other variables. A variable-centered approach generally indicates that trait M correlates with trait Z in a population. In contrast, the person-centered approach can identify the subgroups in this population in which traits Z and M occur together and other subgroups in which these traits are absent.

Person-centered analyses can be performed in various ways. The most common are Cluster Analysis and Latent Profile Analysis (LPA). LPA has many advantages over Cluster Analysis. It is a model-based technique that uses various statistical indices to determine the most appropriate model (Morin et al., 2016). Because of these features, LPA was preferred in this study.

Participants

The study group included 397 students studying at a state university in the southeast of Turkey in 2021. Of all the participants, 239 (60.20%) were female, and 158 (39.80%) were male.

Data Collection Tools

Student Engagements Scale: The scale, developed by Sun and Rueda (2012) and adapted to Turkish by Ergün and Koçak-Usluel (2015), measures students' engagement in online learning environments. The scale consists of 19 items in three sub-dimensions: behavioral engagement, affective engagement, and cognitive engagement. The internal consistency values were .90 for the whole scale, .62 in the behavioral dimension, .90 in the affective dimension, and .86 in the cognitive dimension.

Online Self-regulation Questionnaire: This scale, whose short form was developed by Barnard et al. (2008) and adapted into Turkish by Kilis and Yıldırım (2018), measures students' self-regulation skills in online learning environments. The scale consisted of six sub-dimensions and a total of 24 items. The sub-dimensions of the scale were "Goal Setting", "Environmental Structuring", "Task Strategies", "Time Management", "Help-Seeking", and "Self-evaluation". While Cronbach's alpha coefficient for the whole scale was found to be 0.95, it ranged from .67 to .87 for the sub-factors.

Learning Management System Acceptance Scale (LMSAS): This scale developed by Sezer and Yilmaz (2019) measures students' acceptance of the Learning Management System. The scale consisted of four sub-dimensions with 21 items in total: performance expectation, effort expectancy, facilitating conditions, and social influence. The Cronbach's alpha (α) coefficient for the factors of the scale ranged from .77 to .82.

Data Analysis

The analyses were carried out in two stages. In the first stage, separate LPA models were formed for male and female students. The Mplus 8.3 software (Muthén & Muthén, 1998–2012) and the Maximum Likelihood Ratio (MLR) method were used for the analyses. Mplus provides a number of fit statistics to determine the most appropriate model in LPA. The number of models in LPA is increased iteratively until the

best-fit statistics are obtained. In this study, the Akaike Information Criteria (AIC) (Akaike, 1987), Bayesian Information Criteria (BIC) (Schwartz, 1978) and adjusted BIC indices (SABIC) (Sclove, 1987) were taken into account to determine the most appropriate number of profiles. Lower values for these indexes represented the best fit. In addition, Lo-Mendell-Rubin Likelihood Ratio Test (LMR) and Bootstrap Likelihood Ratio Test (BLRT) were used for each model. These fit indices yield a significant p-value (Indicating whether the k-profile model is superior to the k-1 profile model) for both tests (McLachlan & Peel, 2000). Lastly, Entropy and posterior probabilities were evaluated to determine how accurately the sample was assigned to the profiles (Nylund et al., 2007). Entropy is used to test the accuracy of classification (Lubke & Muthén, 2007). Specifically, Entropy indicates that the models with high values (from 0 to 1) have less classification errors. Nylund et al. (2007) state that when determining the optimal model, not only the fit statistics but also the profile size and distinctiveness should be examined. As the number of profiles increases, the fit statistics give better results, yet these results usually have very close values. Accordingly, all these factors were considered when choosing the final model for the study.

In the second stage, a multigroup LPA was performed to assess profile similarity within the sample. As in measurement invariance analysis, Explanatory similarity is a sequential process. On the other hand, Morin et al. (2016) identified a six-step procedure for assessing group similarities and differences in person-centered approaches. For the sample, a configural similarity model that allows each indicator's parameters to be freely estimated is established. In the second step, a structural similarity model in which the mean of each indicator in the parameters is fixed to be equal across samples is established. In the third step, a dispersion similarity model in which the variances of each indicator in the parameters are fixed to be equal across samples is established. In the fourth step, a distributional similarity model in which the number of individuals in each profile is fixed to be equal across samples is established. The fit indices of the last three models, in which the parameters are fixed equally across samples, are compared with the fit indices of the first estimated free model. In the fifth and sixth steps, distal outcomes are added to the appropriate model determined to test the Explanatory Similarity. Two models in which distal outcome means are freely estimated and fixed equally for each profile are established, and these models are compared with each other.

FINDINGS

The fit statistics for the 2- to 6-profile solutions for both male and female students can be seen in Table 1. When these models were examined among themselves, it was seen that all the fit indices continued to decrease as the number of profiles increased. When the third and fourth models were evaluated, it was seen that the LMR value lost its significance after the 3rd model. When the second and third models were compared, it was seen that all the fit indices of the third model were lower than the fit indices of the second model. The configural similarity test was supported when the 3-profile solution was considered optimal for male and female students. For this reason, a three-profile model was preferred.

A configural similarity model was applied as the decision made was that the three-profile model was suitable for male and female students. The fit statistics for the models testing the configural similarity model and the other three forms of invariance (structural, dispersion, and distributional) are presented in Table 2. When the configural similarity and structural similarity models were compared, it was revealed that the structural similarity model had a lower BIC value and therefore provided a better fit. Next, the dispersion similarity model and the structural similarity model were compared, and it was found that the dispersion similarity model had better fit indices. Lastly, it was revealed that the distributional similarity model showed better fit statistics than the dispersion similarity model. Accordingly, the decision was that distributional similarity was the most appropriate solution for male and female students.

Table 1. Model Fit Statistics For 2- To 6-Profile Models

Class Female	k	LL	#fp	AIC	BIC	SABIC	Entropy	LMR	BLRT
1 Profile	1	-1301.388	8	2618.775	2646.587	2621.229	-	-	-
2 Profiles	2	-1021.530	13	2069.061	2114.255	2073.049	0.904	<=.001	<=.001
3 Profiles	3	-911.688	18	1859.375	1921.952	1864.897	0.908	<=.001	<=.001
4 Profiles	4	-841.540	23	1729.080	1809.039	1736.135	0.922	>.001	<=.001
5 Profiles	5	-812.065	28	1680.130	1777.471	1688.719	0.920	>.001	<=.001
6 Profiles	6	-788.396	33	1642.791	1757.514	1652.914	0.952	>.001	<=.001
Class Male	k	LL	#fp	AIC	BIC	SABIC	Entropy	LMR	BLRT
1 Profile	1	-941.764	8	1899.529	1924.030	1898.706	-	-	-
2 Profiles	2	-709.051	13	1444.102	1483.916	1442.765	0.948	<=.001	<=.001
3 Profiles	3	-580.573	18	1197.147	1252.274	1195.295	0.924	<=.001	<=.001
4 Profiles	4	-517.421	23	1080.843	1151.283	1078.477	0.952	>.001	<=.001
5 Profiles	5	-494.006	28	1044.011	1129.764	1041.131	0.949	>.001	<=.001
6 Profiles	6	-465.811	33	997.622	1098.687	994.226	0.976	>.001	<=.001

Table 2. Invariance Test Statistics For The Three-Profile Model

Cross-Gender Similarity	k	LL	#fp	AIC	BIC	SABIC	Entropy	LMR	BLRT
Configural	3	-1683.731	53	3473.462	3684.611	3516.440	0.959	-	-
Structural (Means)	3	-1717.902	41	3517.804	3681.145	3551.051	0.952	-	-
Dispersion (Means & Variances)	3	-1722.416	29	3502.831	3618.365	3526.347	0.952	-	-
Distributional (Means, Variances, Probabilities)	3	-1724.103	27	3502.206	3609.772	3524.100	0.952	-	-

Profile Features

Profile-1 (very low LMS Acceptance): Compared to the other profiles, the students in this profile had very low LMS acceptance and subscale scores. They scored lowest from the effort expectancy subscale. In other words, they agreed at most that LMS was not easy to use. This profile constituted 15.3% of the whole sample. There were 8% girls and 7.3% boys in the profile.

Profile-2 (Low LMS Acceptance): The students in this profile had low LMS acceptance and subscale scores. They also got the lowest score from the performance expectancy subscale. In other words, they agreed at most that LMS was not useful. This profile constituted 36% of the whole sample. There were 23.4% girls and 12.6% boys in the profile.

Profile-3 (High LMS Acceptance): The students in this profile had higher LMS acceptance and subscale scores than those in the other profiles. They scored highest from the performance expectancy subscale. In other words, they agreed at most that LMS was useful. This profile constituted 48.6% of the whole sample. There were 28.7% girls and 19.9% boys in the profile.

The characteristics of the Latent Profiles and the distribution of the profiles by gender can be seen in Figure 1 and Figure 2.

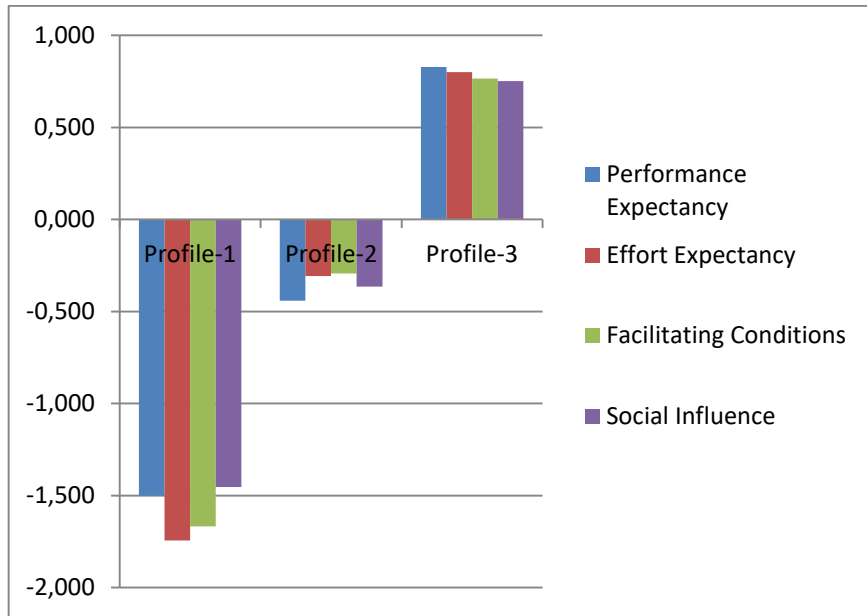


Figure 1. Characteristics of the Latent Profiles

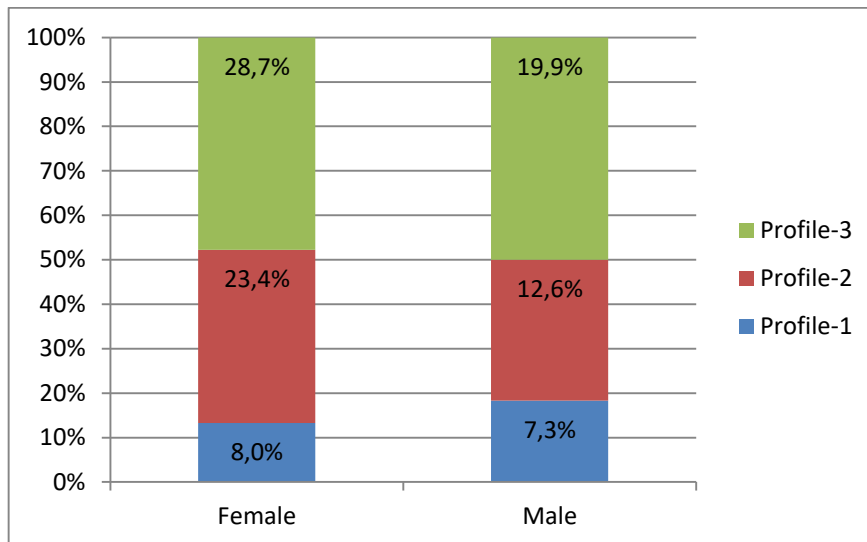


Figure 2. Profile Distributions by Gender

Findings for the Distal Outcomes

Explanatory similarity results for distal outcomes are given in Table 3. The distal outcomes (online engagement and online self-regulation) were added to the established model to test the explanatory similarity model. Later, the Freely Estimated Across model was formed for male and female students using both distal outcomes. This model was compared to the Equality Across model. As shown in Table 3, compared to the Freely Estimated Across model, it was revealed that the Equality Across model had a lower BIC value and that the AIC and SABIC values were quite similar. Therefore, these results supported the explanatory similarity model. Lastly, the multivariate delta method (MODEL CONSTRAINT command in Mplus) was used to systematically test the mean level differences between male and female students (Raykov & Marcoulides, 2004). Afterwards, when the profiles of the male and female students were compared within themselves and with each other, a Wald chi-square analysis was conducted to determine whether there was a significant difference between the distal outcome mean scores. The results of the Wald chi-square analysis can be seen in Table 4.

Table 3. Explanatory Similarity Results For Distal Outcomes

Explanatory Similarity: Outcomes	k	LL	#fp	AIC	BIC	SABIC	Entropy	LMR	BLRT
Freely Estimated Across Gender	3	-2506.922	51	5115.843	5319.024	5157.200	0.947	-	-
Equality Across Gender	3	-2510.125	45	5110.249	5289.526	5146.740	0.947	-	-

Table 4. Wald Chi-Square Test Results For The Distal Outcomes

	Female						Wald-Test
	Profile-1(1)		Profile-2 (2)		Profile-3 (3)		
	M	SD	M	SD	M	SD	
Online Self-regulation	1.823	0.134	3.220	0.123	3.883	0.130	3>2>1
Engagement in online learning environments	2.184	0.098	3.171	0.126	4.011	0.101	3>2>1
	Male						Wald-Test
	Profile-1(1)		Profile-2(2)		Profile-3(3)		
	M	SD	M	SD	M	SD	
Online Self-regulation	1.888	0.122	3.362	0.089	4.069	0.164	3>2>1
Engagement in online learning environments	2.292	0.122	3.159	0.091	4.137	0.153	3>2>1

The Wald chi-square test, which was conducted to evaluate the female and male profiles within themselves, was found that the lowest mean score obtained from the scales of online engagement and online self-regulation for both male and female students was related to Profile-1 and that the highest mean score was related to Profile-3.

When the male and female profiles were compared with each other, the mean scores regarding online self-regulation (Wald $X^2=0.135$; $p>0.05$) and online engagement (Wald $X^2=0.507$; $p>0.05$) in Profile-1, online self-regulation (Wald $X^2= 1.660$; $p>0.05$) and online engagement (Wald $X^2= 1.378$; $p>0.05$) in Profile-2 and online self-regulation (Wald $X^2=1.063$; $p>0.05$) and online engagement (Wald $X^2=0.013$; $p>0.05$) in Profile-3 did not differ based on gender.

DISCUSSION

In this study, the university students who continued their distance education and used LMS were classified based on gender considering the four factors of the UTAUT model, and their LMS acceptance profiles were defined. The study also examined the extent to which these profiles had a relationship with the students' online self-regulation and engagement in online learning environments. As a result of the research, three profiles were determined as “very low LMS acceptance”, “low LMS acceptance”, and “high LMS acceptance”. Similarly, Garone et al. (2019), using Cluster Analysis, analyzed instructors' LMS usage according to the UTAUT model. As a result of the research, three profiles were determined: high, medium and low. These profiles were named “the early adaptors”, “the early majority” and “the late majority”, respectively. The present study also revealed that more than half of the students (51.3 %) had low LMS acceptance. On the other hand, it was seen that the profile with the highest number of participants belonged to the students with high LMS acceptance (48.6%). In a study conducted with nursing students in Turkey, it was seen that the acceptance perceptions of the students towards LMS were moderate (Sezer et al., 2022).

When the profile distributions of the students with high LMS acceptance were examined for their gender, it was found that the female students (28.7%) were more in this profile than the male students (19.9%). This situation shows that the proportion of female students was higher among those with high LMS acceptance. In previous studies on e-learning environments, Johnson (2011) stated that girls communicated online more than boys, had more social presence, were more satisfied with online courses and found the courses more valuable. In addition, it was reported that women exhibited a higher degree of satisfaction with online learning (González-Gómez et al., 2012). In the UTAUT model, social influence and effort expectancy were stronger predictors of IT use intention for women, while performance expectancy was a stronger predictor of IT use intention for men (Venkatesh et al., 2003). In a study using the TAM model as a theoretical framework, it was stated that girls had higher scores on the scales of behavioral intention and use, perceived ease of use and perception of external control than boys did (Ramirez-Correa et al., 2015). In some studies, it was seen that the female students' mean scores regarding LMS acceptance were statistically significantly higher than those of the male students in terms of total scores and other sub-dimension scores, except for the sub-dimension of social influence (Sezer et al., 2022). Similarly, girls had significantly better mean scores regarding the facilitating conditions than boys (Ibrahim et al., 2021). On the other hand, different results were obtained in some studies. For example, Teo et al. (2015) revealed that gender groups did not statistically differ in perceived usefulness, attitudes towards technology, and intention to use technology. However, the female preservice teachers had lower scores regarding perceived ease of use. Accordingly, the researchers stated that using technology was more difficult for female preservice teachers.

A comparison of the students concerning gender revealed no significant difference between the mean scores of online self-regulation and engagement in all the profiles. When the male and female students were evaluated separately in terms of gender, the lowest mean scores obtained from the online self-regulation scale for both boys and girls were related to the profile of "very low LMS acceptance" (Profile-1) and the highest online self-regulation mean scores were related to the profile of "high LMS acceptance" (Profile-3). Some studies in the literature supported the findings of the present study. For instance, in one study, Zhou et al. (2021) stated that students' online self-regulated English learning strategies in the forethought, performance and self-reflection process were positively and significantly affected by their behavioral intentions towards using e-learning systems. In another study, Chen and Hwang (2019) found that in terms of metacognition and motivation, self-regulation had a positive relationship with performance expectancy, effort expectancy, and social influence. The researcher also stated that performance expectancy, effort expectancy and motivation significantly and directly affected students' intention to use online courses. Similarly, Al-shaikh et al. (2022), in their research on e-learning environments, found that self-regulation had a positive relationship with perceived ease of use and usefulness. Users who feel autonomous and competent in IT use are more willing to continue using IT because these basic needs affect their intrinsic and extrinsic motivations, perceived usefulness and perceived playfulness (Roca & Gagne, 2008).

Similarly, when the male and female students were evaluated separately based on gender, it was seen that the lowest mean scores obtained from the online learning environment engagement scale for both boys and girls were related to the profile of "very low LMS acceptance" (Profile-1) and that the highest online engagement mean scores were related to the profile of "high LMS acceptance" (Profile-3). Similar findings were obtained in a study conducted by Moldonado et al. (2011) using the UTAUT model. Moldonado et al. (2011) found that e-learning motivation positively affected behavioral intention towards the e-learning portal. In studies conducted with the TAM model, it was revealed that perceived ease of use, perceived usefulness, and behavioral intention to use had a positive effect on students' engagement in the mobile-based assessment application (Bacca-Acosta & Avila-Garzon, 2021). Similarly, Lin (2009) stated that individuals with higher cognitive absorption experience (state of deep engagement with the virtual community) in the virtual community might have more positive perceived usefulness and ease of use beliefs. Other studies on LMS acceptance revealed that high perceived usefulness and ease of use effectively increased university students' engagement (Cigdem & Ozturk, 2016; Ustun et al., 2021). In this respect, design quality can affect students' engagement in and acceptance of e-learning systems. For example, Faisal et al. (2020) stated that communication, aesthetics and information quality were strong predictors of both cognitive and affective engagement. In addition, the researchers pointed out that font quality and user control positively affected cognitive engagement and that navigation quality and responsiveness were

important indicators of emotional involvement. Lastly, they stated that cognitive and emotional involvement equally contributed to determining the intention to use e-learning applications.

CONCLUSION AND RECOMMENDATIONS

There are many studies conducted with university students on e-learning acceptance. However, these studies did not focus on e-learning acceptance profiles but examined various factors as predictors of behavioral intention to use and actual use of e-learning systems. In this respect, this study contributes to the related literature. In addition, this study will help the university administration (where the study was conducted) to provide information about student profiles for LMS use. It will be an incentive to evaluate whether the current LMS (ALMS) system's performance meets the goals.

The study revealed that low online self-regulation and engagement in the online learning environment had a relationship with a student profile with very low LMS acceptance and that high online self-regulation and engagement had a relationship with a high LMS acceptance profile. The literature reported that performance expectancy and effort expectancy, the components of the UTAUT model, had a relationship with self-regulation (Chen & Hwang, 2019). In addition, the use of appropriate visual information and interaction aspects in online learning systems increases students' engagement in online learning systems (Cigdem & Ozturk, 2016; Faisal et al., 2020), and this positively affects the maintenance of constant intention to use (Faisal et al., 2020). An LMS's ease of use and usefulness can add value to the existing system by increasing students' acceptance of the LMS as an e-learning system (Hwa et al., 2016). The success of e-learning systems ultimately depends on the successful functioning of online learning courses and the degree of students' acceptance. In this respect, higher education institutions should create user-friendly online courses by considering the design quality while developing online learning resources, and developers should include multimedia features that increase individuals engagement. Instructors, another stakeholder, are recommended not only to use the interaction and multimedia options of the systems more frequently in a way that can support students' self-regulation and engagement in learning but also to improve interaction opportunities within the system by providing frequent feedback on students' work, supporting them and answering their questions. In this way, they can contribute to students' acceptance of LMS by helping them better organize their time and manage their course content in online environments.

LIMITATIONS AND FUTURE RESEARCH

This study had several limitations. Firstly, the study was carried out with university students studying at a university in Turkey. Therefore, the results may not be generalized to other student groups, which may reduce the applicability of the findings to other settings. Secondly, the present study was limited to the students' use of ALMS as an LMS in the distance education process. Different interfaces, features and interaction tools of other LMS applications, such as Moodle and Blackboard, can make a difference in students' LMS acceptance. Third, the type of devices students use to connect to the LMS (mobile devices, computers) may affect their acceptance and engagement in LMS. For this reason, the role of device type could be included in future research. In addition, educational institutions using different LMS applications can be included in future research. Lastly, the study revealed that more than half of the students had low LMS acceptance. In this respect, qualitative studies focusing on the causes of this situation could be carried out in the future.

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