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An analysis of the learning styles in online environments of graduate students studying distance education

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Abstract

This research was conducted with the purpose of analyzing the learning styles in online environments of students in the Anadolu University Institute of Social Sciences distance education non-thesis Master's program. To this end, a quantitative cross-sectional screening model was applied to a total of 271 students in the distance education non-thesis Master's degree program. The data for the study was gathered online using the "E-Learning Styles Scale for Electronic Environments". Some of the findings of the study are as follows: (1) The learning styles in online environments of students do not show statistically significant differences based on sex, income, and average daily use of technological devices. (2) Age appears to have a high level of influence on the visual and aural learning levels of students in online environments and a medium level of influence on their active learning levels. (3) Students who are retired have lower levels of audiovisual learning and active learning compared to students in other vocational groups. (4) As the technology use efficacies of students increase, their logical learning levels in online environments increase. (5) Students who use technological devices for an average of seven or more hours per day have higher independent learning levels in online environments compared to those who use them between 0-3 hours.

Introduction

One of the most important factors that influence the learning of students in online learning environments, along with the effectiveness and efficiency of an online class, is learning styles (Birdal, 2022; Fatahi et al., 2016; Kurnaz & Ergün, 2019; Mutluay, 2018; Uçar, 2022). Kolb (1984) defined learning style as an individual and independent way of learning based on the requirements of the environment in which learning will take place, along with learning experiences acquired through previous learning processes. Learning styles are important for students in order for them to adapt their own cognitive, affective, psychomotor skills and learning experiences to the activities they are expected to execute throughout the online course process (Gülbahar & Alper, 2014). Another definition of learning styles that emphasizes this importance is that it is an indicator of how a student perceives, processes, understands, interprets and memorizes information and is influenced by intellectual, physical, emotional, social, mental, environmental, and cultural factors (Kadam et al., 2021). Learning style is an individual difference that influences the learning requirements and preferences of students throughout the process of acquiring, processing and interpreting information which differentiates them from other students (Şimşek, 2004).

One of the most significant individual differences that influence learning processes while supporting the academic achievements and learning permanence of students is learning styles (Arslan & Uslu, 2014; Fatahi et al., 2016; Kadam et al., 2021; Şimşek, 2004). Yurdal et al. (2021) state that online learning environments are better than face-to-face learning environments for students with different learning styles. Learning in online learning environments, within the capabilities of distance education, takes place in different learning styles and, more significantly, at the pace of the learners themselves (Moore & Kearsley, 2012). From this perspective, it may be stated that learning styles are highly important for learning itself (Özonur et al., 2020). When online learning environments are designed in accordance with the learning styles of students, the motivation, joy, and participation of learners increases, their learning develops (Latham et al., 2012), their academic achievement increases (Kurnaz & Ergün, 2019), and a more effective learning experience is provided (Özonur et al., 2020).

Based on the definitions and findings of the literature on online learning styles provided above, it is understood that as an individual and independent way of learning, learning styles are an individual difference that influences the quality, effectiveness and efficiency of learning experiences and activities to be conducted by students in learning environments while it increases their learning motivations, participation in learning activities and academic achievement.

In situations where learning takes place in online learning environments rather than face- to-face learning environments, the learning experiences to be executed by students will change depending on the opportunities and facilities presented to the student by the online learning environments (Oktay, 2022). The changing roles of students in face-to-face and online learning environments may cause differences in students' learning styles (Badge et al., 2012). Therefore, students will feel the need to develop different learning styes in online learning environments compared to face-to-face learning environments (Özonur et al., 2020). Based on this requirement expressed in the literature, a new definition has been adopted: e-learning styles are learning characteristics that aid students in effectively using the information they require with their own unique learning method in online learning environments (Gülbahar & Alper, 2014).

Gülbahar and Alper (2014) stated that e-learning styles of students may be listed as follows: audiovisual learning, where students learn best through seeing and hearing; logical learning, where students learn through problem solving resulting in detailed and deep thought; independent learning, where students learn individually at their own pace; intuitional learning, where students learn by association with feelings and emotions; verbal learning in which learning takes place through reading; social learning in which interaction is established with other students and learning takes place collaboratively within group work; and active learning in which students learn by doing, living, and experiencing.

One of the significant ways of increasing effectiveness, efficiency and quality in online learning is to design the online learning environments in accordance with the e-learning styles of the students (Birdal, 2022). In online learning environments where learners are responsible for their own learning, determining the learning styles of students assist in discovering the strengths and weaknesses of their learning experiences and makes them prone to learn easily and permanently (Dağ & Geçer, 2009). Thus, designing online learning environments taking students' e-learning styles would increase the effectiveness of personalized educational programs (Yurdal et al., 2021).

Students' learning styles should be determined and analyzed, and the learning processes and environments should be planned and designed based on their learning styles (Evin-Gencel, 2007). Therefore, it is important that when adaptive online learning environments uniquely differentiated by students' learning styles are being designed, the e-learning styles of students are known, and the online learning environments are differentiated in accordance with these e-learning styles (Oktay, 2022).

This study focuses on the e-learning styles of non-thesis Master's degree students studying through distance learning at the Anadolu University Institute of Social Sciences. Students take online courses in virtual classrooms on the Canvas Learning Management System (LMS) in the evening hours under the guidance of an instructor. The classes start between six and ten p.m. and are conducted by turning on the cameras and microphones of the instructor and students. Since these students are mostly employed, these classes are held in the evening hours. Online courses are usually conducted with a lecture by the instructor and a question-and-answer session at the end of the lecture.

This review of the literature revealed no study on determining the e-learning styles of graduate students in online environments. Within the scope of this study, data was

gathered from graduate students studying in the distance education non-thesis program distance learning setting, and the gap in the literature may be filled to a degree.

Research purpose

The purpose of this research is to analyze the learning styles of non-thesis Master's students studying at a distance in online learning environments regarding different variables. To achieve this goal, answers to the following research questions were sought:

1. Do the e-learning styles of students in the Distance Education Non-Thesis Master's Degree programs vary based on gender?
2. Do the e-learning styles of students in the Distance Education Non-Thesis Master's Degree programs vary based on age?
3. Do the e-learning styles of students in the Distance Education Non-Thesis Master's Degree programs vary based on occupation?
4. Do the e-learning styles of students in the Distance Education Non-Thesis Master's Degree programs vary based on monthly income?
5. Do the e-learning styles of students in the Distance Education Non-Thesis Master's Degree programs vary based on technological competence?
6. Do the e-learning styles of students in the Distance Education Non-Thesis Master's Degree programs vary based on the average daily use duration of technology?

Method

The study was conducted using the quantitative method of descriptive research. Descriptive research is a method used when a subject is to be studied as is in order to determine the current apparent status (Karakaya, 2014). In this method, a current situation is explained as carefully as possible, and relationships between events are determined (Büyüköztürk et al., 2014). This method attempts to define the subject of the research by evaluating individuals, events or objects within their own current circumstances (Karasar, 2012).

Research design

This study was conducted in order to analyze different variables of the online environment learning styles of students studying at the Anadolu University Institute of Social Sciences Distance Education Non-Thesis Master's Degree program. One of the general screening models, a cross-sectional screening model, was used in the study. Screening models, which are an integral part of the descriptive method, are ways of organizing a population or sample to gain a general impression regarding a population when the population consists of many elements (Karasar, 2012). Cross-sectional screening models, however, deal with large sample sizes containing individuals with different qualities. In this model, the variables within the study that are to be described are measured all at once (Büyüköztürk et al., 2014; Fraenkel & Wallen, 2006). In this study, in order to determine the online learning styles of non-thesis Master's students studying via distance education based on different variables in a single pass, a cross-sectional screening model was used.

Study group

The population of the study consisted of students studying in the Anadolu University Institute of Social Sciences Distance Education Non-Thesis Master's program during the 2022-2023 educational year. The sample consisted of 271 students who responded to the data gathering tool distributed to all of the students of the program. The non-random method of convenience sampling was used when establishing the sample group of the study. Based on the principles of availability and accessibility, this sampling method saves time and cost to the researcher allowing for rapid data gathering (Büyüköztürk et al., 2014). Researchers who use this method work with voluntary participants (Erkuş, 2005). The demographic characteristics of the students who constitute the workgroup of the study are presented in Table 1.

Table 1. Demographic information of students.

Feature	Variable	N	%
Sex	Female	146	53.9
	Male	125	46.1
Age	18-34	142	52.4
	35-54	121	44.6
	55-64	8	3.0
Occupational Status	Unemployed	34	12.5
	Public Employee	121	44.6
	Private Sector Employee	93	34.3
	Retired	9	3.3
	Self-Employed	14	5.2
Monthly Income	5500 TRY and below	36	13.3
	5501-9999 TRY	82	30.2
	10000 TRY and above	153	56.5
Technology Use Competence	Basic Level	27	10.0
	Medium Level	136	50.1
	Advanced Level	108	39.9
Average Daily Usage Time of Technological Devices	0-3 hours	42	15.5
	3-5 hours	70	25.8
	5-7 hours	73	26.9
	7 and above hours	86	31.8

Data collection tools

Data were gathered for this study using a personal information form and the E-Learning Styles for Electronic Environments Scale' developed by Gülbahar and Alper (2014). The data gathering was conducted electronically. The electronic questionnaire created using Google Forms was distributed to the students in the Anadolu University Institute of Social Sciences Distance Education Non-Thesis Master's programs between November 14, 2022, and January 5, 2023. The electronically created questionnaire was sent to the students' e-mail addresses using shortened links. The voluntary participants were limited to a single response to the questionnaire, and the necessary information was presented to the participants in advance. Care was taken to avoid a biased sample group of participants. Data from participants who did not express their consent of free and voluntary participation were considered false and omitted from the study. A pilot study with 68 participating students was conducted to test the validity and reliability of the data-gathering tools. The pilot study was also conducted in a similar fashion using Google Forms, while the main study utilized data from a total of 271 participants.

Personal information form

The personal information form was created to determine the demographic characteristics of participants, such as sex, age, occupation, income, technology competence, and daily technology use duration.

E-learning styles for electronic environments scale

This measure used in the study was developed by Gülbahar and Alper (2014) and consists of seven sub-factors: "Audiovisual Learning", "Verbal Learning", "Active Learning", "Social Learning", "Independent Learning", "Logical Learning", and "Intuitional Learning". The scale, as a whole, measures the learning styles of individuals in online environments. The scale consists of 38 items and seven sub-factors and is of the 5-point Likert type. Items 1 through 8 measure the audiovisual learning levels of students while items 9-15 measure their verbal learning, 16-21 measure their active learning, 22-27 measure their social learning, 28-31 measure their social learning, 32-34 measure their logical learning, and 35-38 measure their intuitional learning levels. Exploratory factor analysis (EFA) was conducted to test the reliability and construct validity of the scale. Prior to the EFA, the fit of the data was tested, and a Kaiser-Meyer-Olkin (KMO) value of 0.960 was calculated, while the Bartlett test of sphericity was statistically significant ($p<0.01$). The EFA did not reveal any unloaded factor, and 18 of the factors with loading under 0.30 were omitted from the analysis. Next, confirmatory factor analysis (CFA) was conducted, and the analysis revealed that the scale in question could be successfully applied to the students. Additionally, the reliability of the scale was tested using Cronbach's Alpha internal consistency test, and a value of $\alpha= 0.94$ was observed for the whole scale. Furthermore, the Cronbach's Alpha values for the seven sub-factors that the scale consists of were determined to be between 0.72 and 0.87.

Since this study was conducted on a different population, the construct validity and fit values were determined again using CFA. The scale was confirmed on a separate group of students with similar characteristics prior to being applied to the main sample. Using AMOS 21.0 (Analysis of Moment Structures) software, the CFA revealed a good fit statistical value of corrected chi-square $\chi 2/sd = 1.471$. Kline (2011) states that a value between $0 \leq \chi 2/sd \leq 2$ indicates perfect fit. Therefore, the value obtained for this study presents a good fit value. Additionally, RMSEA was calculated as a separate measure of fit. The analysis provided an RMSEA value of 0.042, while the literature indicates a value between .00 and .05 would provide a perfect fit interval (Browne & Cudech, 1993). Studying other goodness of fit indexes resulted in a Comparative Fit Index value calculation of 0.907. Baumgartner and Homberg (1996), and Bentler and Bonett (1980) stated that a value of $.90 \leq CFI \leq .95$ is an acceptable fit measurement. As such, the value calculated for this study was also deemed acceptable. Another goodness of fit index that was calculated was the Tucker-Lewis Index. This value was calculated to be TLI = 0.904. Byrne (1994) stated that this value must be at least 0.90, indicating that the TLI value obtained from the CFA is acceptable. The incremental fit index was determined to be IFI = 0.909. Bollen (1989) stated that a value above 0.90 for this index indicates a good fit. Within this study, the adjusted goodness of fit index was also calculated, resulting in a value of AGFI = 0.850. Shermelleh-Engel and Moosbrugger (2003) stated that the acceptable range of values for this index is $.85 \leq AGFI \leq .90$, resulting in an acceptable value for this study. Lastly, the Standardized Root Mean Squared Residual Value was calculated to be SRMR = 0.068, with Hu and Bentler (1999) stating that a value below .080 is the requirement for a good fit. To determine the reliability of the scale used in the study, the Cronbach's Alpha (α) value of the internal consistency test was conducted, resulting in an internal consistency coefficient of α=0,807 and reliability coefficients for the sub-factors of the scale were all greater than 0.70.

Ethical statement

The E-Learning Styles in Electronic Environments Scale used in the study was developed by Gülbahar and Alper (2014). The required permission for the use of this scale in this study was obtained from the researchers via e-mail, and the study was conducted with the approval of the Anadolu University Humanities and Social Sciences Research and Publication Ethics Committee number E-54380210-050.99-432702 dated 27 October 2022.

Data analysis

The data gathered electronically for the study was first input into the Microsoft Excel spreadsheet program to organize it in order for the data to be successfully analyzed by IBM's SPSS 26.0 software. The organized data were coded in accordance with their responses to the personal information form and the e-learning styles for electronic environments scale and input into SPSS. A total of 296 participants in the voluntary questionnaire were identified. However, 25 of these participants did not provide their explicit consent to

the questionnaire and were therefore considered invalid and removed from the study. Thus, 271 questionnaires were included in the analysis after verifying that all the data was correctly entered and normality analysis was conducted. The kurtosis, skewness, z scores and histograms of the data were analyzed to determine whether or not normal distribution was achieved. With a sample size between 50 and 300, z scores should not exceed 3.29 (Kim, 2013). The z scores of the data set were found to be below 3.29, the kurtosis and skewness values were within the -1/+1 interval, and the histogram indicated normal distribution (Huck, 2012). In order to determine the correlation levels between the percentages and scale variables of the data set, various measurement techniques were implemented sequentially, such as frequency analysis, independent samples t-test, and one-way analysis of variance (ANOVA). Parametric and non-parametric tests were conducted after the data set was confirmed to have a normal distribution. The kurtosis and skewness value calculations, determination of z scores, frequency analysis, independent samples t-test, one-way ANOVA and other parametric and non-parametric tests were conducted using SPSS, whereas due to the different populations being analyzed, the CFA was conducted using AMOS 21.0.

During data analysis, a high number of groups causes an increase in the margin of error. Therefore, in order to regulate the alpha value, Bonferroni correction was conducted prior to the multiple comparison tests. Bonferroni correction is a statistical correction conducted with a binary combination formula being applied to the significance coefficient/ group number (Vialatte & Chchocki, 2008). Therefore, the corrected alpha coefficients in multiple comparison tests are calculated to be 0.05/3=0.016 for groups of 3, 0.05/6=0.008 for groups of 4, and 0.05/10=0.005 for groups of 5. These new significance coefficients were utilized as measurements in the multiple comparison tests conducted in the study. To determine the effect sizes of the significant differences, Cohen's d values and eta-squared (η2) values were calculated (Cohen, 1988a; 1988b). In the analysis tables of the sub-factors of the scale used in the study, the sub-factors were summarized in the table as audiovisual, verbal, active, social, independent, logical, and intuitional. These refer to the following sub-factors of students' learning levels respectively: audiovisual learning levels, verbal learning levels, active learning levels, social learning levels, independent learning levels, logical learning levels, and intuitional learning levels. The total sum of the sub-factors that consist the scale measures students learning styles in online learning environments.

Results

This section of the study presents the statistical analyses conducted in order to determine the online learning styles of students in the distance education non-thesis Master's program. The findings are presented as tables and interpreted further. Independent samples t-test was conducted to measure any significant difference between the sex of students and their learning styles. The results of that analysis are presented in Table 2.

Table 2. Differentiation of learning styles of students in online environments based on sex.

Sub-factor/ Scale	Sex	N	X̄	sd	T	df	p
Audiovisual	Female	146	4.121	.5198	.364	269	.539
	Male	125	4.098	.5461			
Verbal	Female	146	3.607	.6099	-.034	269	.473
	Male	125	3.610	.6572			
Active	Female	146	3.455	.8054	3.53	269	.163
	Male	125	3.092	.8863			
Social	Female	146	3.679	.8343	-.072	269	.794
	Male	125	3.686	.8703			
Independent	Female	146	3.808	.7422	-.087	269	.185
	Male	125	3.884	.6813			
Logical	Female	146	3.121	.9238	-1.95	269	.717
	Male	125	3.346	.9767			
Intuitional	Female	146	3.429	.7991	1.28	269	.846
	Male	125	3.304	.8023			
Total	Female	146	3.667	.4682	.822	269	.823
	Male	125	3.618	.4950			

Based on the information presented in Table 2, the learning styles of students in online learning environments did not statistically significantly differ based on sex: audiovisual learning (t(269)= 0.364, p>0.05), verbal learning (t(269)= -0.034, p>0.05), active learning (t(269)= 3.530, p>0.05), social learning (t(269)= -0.072, p>0.05), independent learning (t(269)= -0,087, p>0.05), logical learning (t(269)= -1.950, p>0.05) and intuitional learning (t(269)= 1.280, p>0.05). Similarly, the total scores of the students in online environments obtained from the learning styles scale did not result in statistically significant differentiation based on sex as a variable (t(269)= 0.822, p>0.05). This situation indicates that sex is not an influential variable in the learning styles of students in online learning environments. The result of the analysis did not reveal any significant difference, and therefore Cohen's d value was not recorded.

One-way ANOVA was conducted to determine if statistically significant differences existed between students' online environment learning styles and age. The findings of this test are presented in Table 3.

Table 3. Differentiation of learning styles of students in online environments based on age.

Sub-factor/ Scale	Variables (ages)	N	X̄	Sd	df	F	p	Difference
Audiovisual	18-34	142	4.194	.4628	270	29.80	.000*	18-34 > 55-64
	35-54	121	4.096	.5099				
	55-64	8	2.843	.3644				35-54 > 55-64
Verbal	18-34	142	3.586	.6315	270	.430	.651	-
	35-54	121	3.643	.6289				
	55-64	8	3.482	.7037				
Active	18-34	142	3.478	.7849	270	15.19	.000*	18-34 > 35-54
	35-54	121	3.147	.8730				
			2.020	.4833				18-34 > 55-64
	55-64	8						35-54 > 55-64
Social	18-34	142	3.642	.9102	270	.462	.630	-
	35-54	121	3.736	.7682				
	55-64	8	3.583	.9677				
Independent	18-34	142	3.950	.6679	270	3.467	.033	-
	35-54	121	3.721	.7536				
	55-64	8	3.781	.6870				
Logical	18-34	142	3.293	.8863	270	.766	.466	-
	35-54	121	3.148	1.032				
	55-64	8	3.166	.8728				
Intuitional	18-34	142	3.376	.8114	270	.896	.410	-
	35-54	121	3.390	.8009				
	55-64	8	3.000	.5976				
Total	18-34	142	3.699	.4555	270	6.741	.001*	18-34 > 55-64
	35-54	121	3.617	.4910				
	55-64	8	3.088	.4071				35-54 > 55-64

*p<0.016

Studying the findings in Table 3 shows a statistically significant difference in the learning styles of students in online learning environments based on age (F(2.270)=[6.741], p<0.016). Thus, it may be stated that young and middle-aged students have higher levels of learning in online learning environments compared to students of older ages. An analysis of the sub-factors of the scale indicated significant differences in audiovisual learning levels and active learning levels depending on their ages (F(2.270)=[29.80], p<0.016; F(2.270)=[15.19], p<0.016). In order to determine the source of this difference, first, a Levene test was conducted. The results of the Levene test showed that the requirement of homogenous variances was satisfied. In order to determine which groups were the source of the statistically significant differences, Tukey's range test (Tukey's Honestly Significant Difference – HSD) was applied. The test results indicated that students aged 18-34 ($\bar{X}$= 4.194, sd= .4628) had higher levels of audiovisual learning than those aged 55-64 ($\bar{X}$= 2.843, sd= .3644). Similarly, students aged 35-54 ($\bar{X}$= 4.096, sd= .5099) also had higher audiovisual learning levels compared to those aged 55-64 ($\bar{X}$= 2.843, sd= .3644). No difference was found between students in the young and middle age groups regarding audiovisual learning. Additionally, students aged 18-34 ($\bar{X}$= 3.478, sd= .7849) were found to have higher levels of active learning compared to students aged 35-54 ($\bar{X}$= 3.147, sd= .8730) and 55-64 ($\bar{X}$= 2.020, sd= .4833). Similarly, students aged 35-54 ($\bar{X}$= 3.147, sd= .8730) had higher active learning levels than students aged 55-64 ($\bar{X}$= 2.020, sd= .4833). This finding supports the notion that as age reduces, active learning levels of students in online learning environments increases. In order to determine the effect sizes of the differences obtained in the test, an analysis of the eta-squared (η2) values was chosen. The literature in the field indicates values between 0 and 0.01 as very small effects, 0.01 and 0.06 as small effects, 0.06 and 0.14 as medium effects, and values above 0.14 as large effects regarding effect size ranges (Cohen, 1988b). In this regard, the effect size of age on the audiovisual learning levels of students in online environments was found to be large (η2= 0.181), and medium on active learning levels (η2= 0.101).

One-Way ANOVA test was conducted to determine whether or not students' learning styles in online learning environments differentiated based on occupation, and the results of the test are presented in Table 4.

The ANOVA test results presented in Table 4 were studied, revealing a statistically significant difference in the learning styles of students in online learning environments based on occupation (F(2.270) = [4.885], p<0.005). Similarly, significant differences were recorded in the audiovisual learning and active learning sub-factors. In order to determine the source of the significant differences in both the whole of the online learning differences scale and the sub-factors, Tukey's HSD multiple comparison test was conducted. The analysis revealed that retired students ($\bar{X}$= 3.064, sd= .4019) differed in their online learning styles compared to other students. An analysis of the sub-factors revealed that retired students ($\bar{X}$= 3.097, sd= .6428) had lower levels of audiovisual learning compared to other occupational groups, and a similar situation was observed for active learning and retired students ($\bar{X}$= 2.222, sd= .8036). No statistically significant difference was observed with the remaining sub-factors.

Table 4. Differentiation of learning styles of students in an online environment based on occupation.

Sub-Factor/ Scale	Variables (Occupation)	N	X	sd	df	F	p	Difference
Audiovisual	Unemployed	34	4.220	.4502	270	10.76	.000*	Unemployed> Retired
	Public Sector	121	4.116	.5203				Public S.> Retired
	Private Sector	93	4.186	.4661				Private S.> Retired
	Retired	9	3.097	.6428				Freelance> Retired
	Freelance	14	3.937	.4896				
Verbal	Unemployed	34	3.836	.6041	270	2.401	.050	-
	Public Sector	121	3.628	.6298				
	Private Sector	93	3.569	.6348				
	Retired	9	3.349	.5895				
	Freelance	14	3.316	.5719				
Active	Unemployed	34	3.480	.8058	270	4.223	.002*	Unemployed> Retired
	Public Sector	121	3.305	.8714				Public S.> Retired
	Private Sector	93	3.320	.8213				Public S.> Retired
	Retired	9	2.222	.8036				Freelance> Retired
	Freelance	14	3.131	.8143				
Social	Unemployed	34	3.759	.8868	270	.902	.463	-
	Public Sector	121	3.672	.8868				
	Private Sector	93	3.740	.7568				
	Retired	9	3.296	.8849				
	Freelance	14	3.452	.9987				
Independent	Unemployed	34	4.022	.5271	270	1.541	.191	-
	Public Sector	121	3.754	.8036				
	Private Sector	93	3.924	.6550				
	Retired	9	3.638	.6627				
	Freelance	14	3.767	.6237				
Logical	Unemployed	34	3.245	.8696	270	.755	.556	-
	Public Sector	121	3.305	.9809				
	Private Sector	93	3.157	.9588				
	Retired	9	2.814	.8992				
	Freelance	14	3.190	.9310				
Intuitional	Unemployed	34	3.375	.7468	270	1.509	.200	-
	Public Sector	121	3.431	.8391				
	Private Sector	93	3.387	.7995				
	Retired	9	3.027	.5651				
	Freelance	14	2.964	.6419				
Total	Unemployed	34	3.773	.4207	270	4.885	.001*	Unemployed> Retired
	Public Sector	121	3.654	.5168				Public S.> Retired
	Private Sector	93	3.672	.4147				Private S.> Retired
	Retired	9	3.064	.4019				Freelance> Retired
	Freelance	14	3.439	.4845				

p<0.005

In order to determine the effect size of these significant differences, eta-squared (η2) values were noted. Analysis of these values indicated that occupation had a medium effect size (η2= 0.139) on the audiovisual learning levels of students in online environments, while the effect size on active learning levels was small (η2= 0.059). To determine if the learning styles of students in online environments differed based on income, an ANOVA test was conducted, and the results of the test are presented in Table 5.

Table 5. Differentiation of online learning styles based on monthly income.

Sub-Factor/ Scale	Variables	N	X	sd	df	F	p	Difference
Audiovisual	5500 TRY and below	36	4.197	.4690	270	.829	.438	-
	5500-9999 TRY	82	4.062	.6064				
	10000 TRY and above	153	4.116	.5016				
Verbal	5500 TRY and below	36	3.857	.6296	270	4.170	.016*	5500 TRY and below > 10000 TRY and above
	5500-9999 TRY	82	3.644	.6370				
	10000 TRY and above	153	3.531	.6152				
Active	5500 TRY and below	36	3.518	.7916	270	2.570	.078	-
	5500-9999 TRY	82	3.363	.9619				
	10000 TRY and above	153	3,192	.8100				
Social	5500 TRY and below	36	3.768	.9234	270	.319	.727	-
	5500-9999 TRY	82	3.634	.9043				
	10000 TRY and above	153	3.688	.8042				
Independent	5500 TRY and below	36	3.680	.6697	270	1.760	.174	-
	5500-9999 TRY	82	3.942	.8082				
	10000 TRY and above	153	3.828	.6660				
Logical	5500 TRY and below	36	3.055	.8600	270	.905	.406	-
	5500-9999 TRY	82	3.191	.9399				
	10000 TRY and above	153	3.283	.9813				
Intuitional	5500 TRY and below	36	3.388	.8544	270	.041	.960	-
	5500-9999 TRY	82	3.387	.8714				
	10000 TRY and above	153	3.359	.7537				
Total	5500 TRY and below	36	3.730	.4651	270	.801	.450	-
	5500-9999 TRY	82	3.655	.5652				
	10000 TRY and above	153	3.619	.4331				

p<0.016

Table 5 presents data indicating there was no statistically significant differentiation in the learning styles of students in online environments and income level (p>0.016). A study of the sub-factors revealed a significant difference in students' verbal learning levels in online environments and their income levels (F(2.270)= [4.170], p<0.016). Tukey's HSD was conducted to determine the source of this difference, resulting in students with a monthly income of 5500 TRY and below ($\bar{X}$= 3.857, ss= .6296) having higher verbal learning levels in online environments compared to students with 10000 TRY and above of monthly income ($\bar{X}$= 3.531, sd= .6152). When the eta-squared (η2) values of the observed significant difference are calculated to determine the effect size, the value was found to be η2=0.030 indicating a small effect size. On the other hand, no significant difference was found regarding income influencing the other sub-factors of the scale.

Another ANOVA test was conducted to determine whether a statistically significant difference existed between the learning styles of students in online environments and their technology use competencies. The results of the test are presented in Table 6.

Table 6. Learning style differentiation based on technology use competencies.

Sub-Factor/ Scale	Variables (Competence Levels)	N	X	sd	df	F	P	Difference
Audiovisual	Basic	27	3.717	.7194	270	8.969	.000*	Intermediate > Basic
	Intermediate	136	4.132	.4945				Advanced > Basic
	Advanced	108	4.181	.4828				
Verbal	Basic	27	3.576	.7202	270	.054	.948	-
	Intermediate	136	3.618	.6264				
	Advanced	108	3.604	.6190				
Active	Basic	27	2.864	1.003	270	3.701	.026	-
	Intermediate	136	3.338	.8500				
	Advanced	108	3.330	.8161				
Social	Basic	27	3.530	.8709	270	.922	.399	-
	Intermediate	136	3.745	.7721				
	Advanced	108	3.642	.9339				
Independent	Basic	27	3.481	.7169	270	7.813	.001*	Advanced > Basic
	Intermediate	136	3.773	.7810				
	Advanced	108	4.020	.5679				
Logical	Basic	27	2.370	.6292	270	18.02	.000*	Intermediate > Basic
	Intermediate	136	3.166	.9694				Advanced > Basic
	Advanced	108	3.512	.8603				Advanced >Intermediate
Intuitional	Basic	27	3.037	.6992	270	4.816	.009*	Intermediate > Basic
	Intermediate	136	3.501	.8263				Advanced > Basic
	Advanced	108	3.291	.7646				
Total	Basic	27	3.324	.5452	270	7.023	.001*	Intermediate >Basic
	Intermediate	136	3.670	.4870				Advanced > Basic
	Advanced	108	3.692	.4266				

*p<0.016

Table 6 portrays whether or not the learning styles of students in online environments differ based on ICT us competence, where ICT competence was found to have a statistically significant influence on online learning styles (F(.270)=[7.023], p<0.016). A significant difference was also found when the sub-factors were analyzed. Tukey's HSD test was conducted in order to determine the source of these significant differences, revealing that students with intermediate ($\bar{X}$= 4.132, sd= .4945) and advanced ($\bar{X}$= 4.181, sd= .4828) technology use competencies had higher audiovisual learning levels compared to those with basic competencies ($\bar{X}$= 3.717, sd= .7194). This significant difference had a medium effect size (η2= 0.062). Students with advanced competencies in technology use ($\bar{X}$= 4.020, sd= .5679) had higher levels of independent learning compared to those with basic competencies ($\bar{X}$= 3.481, sd= .7169). This difference, however, had a smaller effect size (η2=0.055). A further significant difference was found in the logical learning sub-factor, where logical learning levels increased as technology competence increased, with a medium effect size (η2=0.118) being calculated for this correlation. Similarly, a significant difference was found where medium ($\bar{X}$= 3.501, sd= .8263) and advanced ($\bar{X}$= 3.291, sd= .7646) ICT competencies led to higher intuitional learning levels compared to students with basic ($\bar{X}$= 3037, sd= .6992) competencies, with a small (η2=0.034) effect size. To determine whether average daily technology use created a significant difference in the online learning styles of students, an ANOVA test was conducted and the findings are presented in Table 7.

Table 7. Differentiation of learning styles of students in online learning environments based on daily average use duration of technological devices.

Sub-Factor/ Scale	Variables (Use Time)	N	$\bar{X}$	sd	df	F	p	Difference
Audiovisual	0-3 hours	42	4.098	.5532	270	1.250	.292	-
	3-5 hours	70	4.075	.5948				
	5-7 hours	73	4.047	.5058				
	7 hours or more	86	4.199	.4821				
Verbal	0-3 hours	42	3.710	.6800	270	1.131	.337	-
	3-5 hours	70	3.655	.6353				
	5-7 hours	73	3.616	.5841				
	7 hours or more	86	3.515	.6397				
Active	0-3 hours	42	3.226	.9793	270	.439	.726	-
	3-5 hours	70	3.228	.8503				
	5-7 hours	73	3.376	.8174				
	7 hours or more	86	3.290	.8545				
Social	0-3 hours	42	3.781	.8035	270	.886	.449	-
	3-5 hours	70	3.545	.8796				
	5-7 hours	73	3.716	.7488				
	7 hours or more	86	3.717	.9249				
Independent	0-3 hours	42	3.452	.9127	270	8.643	.000*	7 hours or more > 0-3 hours
	3-5 hours	70	3.707	.6634				
	5-7 hours	73	3.962	.6047				
	7 hours or more	86	4.043	.6396				
Logical	0-3 hours	42	3.134	.9851	270	.422	.738	-
	3-5 hours	70	3.166	.8695				
	5-7 hours	73	3.237	.9852				
	7 hours or more	86	3.306	.9851				
Intuitional	0-3 hours	42	3.452	.9535	270	.209	.890	-
	3-5 hours	70	3.328	.8215				
	5-7 hours	73	3.373	.6973				
	7 hours or more	86	3.366	.7986				
Total	0-3 hours	42	3.627	.5799	270	.498	.684	-
	3-5 hours	70	3.591	.4713				
	5-7 hours	73	3.666	.4651				
	7 hours or more	86	3.679	.4509				

*p<0.008

A quick glance at the findings of the ANOVA test presented in Table 7 clearly shows no significant difference was found between students' online learning styles and average daily use time of technology (F(2.270)=[0.498], p<0.008). Regarding the sub-factors of the scale, only independent learning revealed a significant difference (F(2.270)= [8.643], p<0.008). To determine the source of this difference, firstly, a Levene test was conducted, resulting in the finding that the variance did not portray homogenous distribution, leading to the necessity for a Games-Howell test. As a result of the non-parametric post hoc multiple comparison, students who used technological devices for seven or more hours during the day were found ($\bar{X}$= 4.043, sd= .6396) to have higher levels of independent learning compared to those who only used them between 0-3 hours per day on average ($\bar{X}$= 3.452, sd= .9127). The effect size of this significant difference was found to be medium (η2= 0.088), while none of the other sub-factors of the scale presented any significant difference.

Discussion

This study analyzed the learning styles in online learning environments of students in a non-thesis Master's program studying through distance education regarding different variables. The analysis resulted in many findings regarding online learning styles.

Firstly, the online learning styles of the participants were analyzed to determine whether they significantly differed based on sex. The results indicate that online learning styles do not differ by sex, and similar findings emerged regarding the other sub-factors of which the scale of measurement consists. This shows that the distance education non-thesis Master's students may have a common learning style regardless of sex. The literature in the field reveals other scientific research that supports these findings (Arslan & Babadoğan, 2005; Birdal, 2022; Demir, 2015; Dikmen, 2020; Mutluay, 2018; Özgür, 2013; Yeşilyurt, 2014). Conversely, there are also studies which have found statistically significant differences in online learning styles of students and their sex (Dikbaş, 2006; Kuru, 2018; Özüdoğru, 2022; Şentürk, 2016; Şentürk & Ciğerci, 2018; Uçar, 2022; Yetiş, 2018).

When a significant difference in the learning styles of students in online environments based on age was sought, a meaningful effect was found between the ages of students and their learning styles (Arslan & Babadoğan, 2005). The findings were that young (18-34) and middle-aged (35-54) students had higher levels of audiovisual learning compared to older (55-65) students. The effect size for this significant difference was also found to be quite large. One consideration may be that changes in the sensory perception and cognition of students as they age may be the cause for this situation, causing differences between students. Additionally, the active learning levels of students aged 18-34 were higher than those of students aged 35-54 and 55-64, and the levels of middle-aged (35-54) students were also higher than the levels of students aged 55-64 indicating an increase in active learning with a decrease of age. This may be caused by the higher capacity to process information of younger individuals, an ability which may decline with age. The effect size of this significant difference was found to be medium, however, studies in the field also indicate no significant difference between age and online learning styles (Özgür, 2013).

A review of the findings regarding the occupation of the participating students shows that occupation causes significant differences in their online learning styles. Retired students were found to have lower levels of active learning compared to students in other occupational groups. The eta-squared (η2) values of these significant differences were studied in order to determine the effect size of this variable. The analysis revealed a medium effect size of occupation on audiovisual learning in online learning environments and a small effect size on active learning. This situation may once again be related to the fact that retired students tend to be older, which would draw parallels to the findings of the age variable.

No statistically significant correlation was found between the monthly incomes of the participating students and their online learning styles. The analysis of the sub-factors of the online learning styles scale revealed a statistically significant difference between monthly income and verbal learning levels. The multiple comparison test conducted to find the cause of this difference revealed that students making 5500 TRY or less had higher verbal learning levels than those earning 10000 TRY or more each month. This may be caused by the need for low-income students to use their verbal skills more in order to communicate and express their thoughts in their daily lives, further developing this learning ability. The eta-squared (η2) value of this difference was analyzed, and a small effect size between the two variables was found.

Another research question this study attempted to answer was whether the learning styles of students in online environments differed based on their competencies in using information and communication technologies. The results show a statistically significant difference in the learning styles of students in online environments and their ICT competencies. This difference was observed to take place in certain sub-factors of the online learning styles scale. The findings were that students with intermediate and advanced technology use competencies had a medium size effect on their online audiovisual learning styles compared to students with only basic competencies. Students with advanced ICT competencies also had higher levels of independent learning compared to those with basic competencies. However, the effect size of this correlation was small. A similar difference was found regarding logical learning levels in that an increase in ICT competence also led to an increase in this style of learning in online environments, with the effect size determined to be medium. Students with intermediate and advanced technology competencies also had higher intuitional learning levels than those with basic competencies. However, the effect size of this significant difference was small. Achieving a certain level of competence when using technology requires not only higher levels of learning skills but also constant active use of technology which is why it is believed that individuals who achieve this level of competence also increase their independent, logical, and intuitional learning levels over time.

Lastly, homogenous differentiation between the average daily technology use of students and their online learning styles was studied. The analysis concluded that the duration for which students used technological devices did not cause any changes in students' online learning styles (Kuru, 2018; Yetiş, 2018). Conversely, studies also exist indicating statistically significant differences in online learning styles based on how long students use technology throughout the day (Mutluay, 2018). Further analysis of the sub-factors only resulted in a statistically significant difference in independent learning. The finding was that students who used technology for seven or more hours a day had higher independent learning levels compared to those who only used them between 0-3 hours on average. No statistically significant difference was found in this regard between students who used technology 3-5 hours a day and 5-7 hours a day. This indicates that heavy (seven hours or more per day on average) ICT users have significant differences regarding their independent learning styles. This significant

difference was found to have a medium effect size.

Limitations of the study

This study has various limitations. Being a study on the learning styles in online learning environments of non-thesis Master's degree students enrolled in distance education, one limitation may be the selection of students enrolled at the Anadolu University Institute of Social Sciences. This study is also limited to the e-learning styles in online environments scale. Additionally, it is limited by the variables being measured, namely sex, age, occupation, income, ICT competence, and daily average technology use duration. The self-reporting nature of the responses to the scale items during the data gathering process may also be considered a limitation. Lastly, the requirement for gathering data through an online environment such as Google Forms due to the global COVID-19 pandemic health crisis may be considered to be a limitation.

Recommendations

Various recommendations may be made based on the outcomes of the study. Studies with larger sample sizes of non-thesis Master's students' learning styles in distance education and online learning environments may be conducted. While this study was conducted on non-thesis distance educated Master's students, various other studies on thesis-required face-to-face Master's students and doctorate students may be recommended. Age appears to be an important factor in online learning styles, with young and middle-aged students having higher levels of audiovisual learning compared to older students. Similarly, retired students were found to have lower levels of audiovisual and active learning levels compared to other occupational groups. Training for older students regarding audiovisual practice and techniques may prove to be beneficial. Lastly, considering technology competence and use time appears to have a positive effect on various sub-factors of online learning styles, a moderated increase in the use of electronic devices such as computers, telephones, and tablets for the purpose of learning may be recommended.

Conclusions

The findings of this study analyzing the learning styles of non-thesis Master's degree students in online learning environments are presented sequentially below.

The learning styles of non-thesis Master's degree students studying through distance education did not differ based on gender. This finding led to the conclusion that non-thesis Master's degree students in distance education had a common learning style regardless of gender, and therefore gender-specific arrangements are not required in the instructional design of learning activities during the development of distance education programs.

The learning styles of non-thesis Master's degree students studying through distance education differed based on age. The findings revealed a decrease in audio-visual and active learning levels as age progressed. This led to the conclusion that age-based learning activities may be effective when designing distance education programs, which would consider the reduction in sensory perception and information processing capacity with age. This conclusion may be supplemented with learning activities that reduce cognitive load and appeal to the available visual, aural and affective perception levels of students in accordance with their ages.

The learning styles of non-thesis Master's degree students studying through distance education differed based on occupation. Similar (and obviously related) to the age variable, retired students were older than students of other occupations resulting in lower levels of audio-visual and active learning. As such, it was concluded that learning activities that reduce the cognitive load and appeal to the visual, aural and affective perception levels of retired students would be beneficial during the instructional design of distance education programs.

A statistically significant difference was found between the verbal learning levels and monthly incomes regarding the learning styles of distance education students in non-thesis Master's degree programs. This difference may be due to lower-income students needing to use their verbal skills to communicate and express their thoughts more frequently in their daily lives. Thus, scholarships and other financial aid may be offered to lower-income students to support their financial status, or they may be provided access to the technology they need. Other preventative measures may be taken, considering the learning styles of low-income students may be negatively impacted by their lack of access to technology.

Technology competence was a statistically significant variable that influenced the learning styles of distance education students in non-thesis Master's programs. Increased competence regarding technology resulted in a medium sized increase in audio-visual learning levels. Achieving a certain level of competence when using technology requires not only higher-level learning skills but also constant and active use of technology. Therefore, it may be stated that individuals who achieve this level of competence eventually also achieve higher levels of independent, logical, and intuitional learning. As such, during the instructional design of distance education programs, more technologically focused environments may be created for students with higher technology competencies. Learning activities may be arranged such that students may indulge in higher levels of interaction with other students, instructors, and content.

The average daily duration of technology use did not result in a significant difference in the learning styles of distance education students in non-thesis Master's degree programs. Despite this, the study revealed that students who used technology for seven hours or more each day had higher independent learning levels compared to those who used technology for only 0-3 hours a day. Extra attention may be paid to certain aspects to accommodate students

with independent learning styles and high durations of technology use. Learning activities that take advantage of self-directed learning skills may be created while preparing learning activities.

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