PROFILING LEARNING PREFERENCES OF DISTANCE EDUCATION STUDENTS BASED ON NEURAL NETWORK ANALYSIS

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ABSTRACT

The learning preferences of the learners are of prime importance in the planning of distance education systems and the design of learning environments. Learning technique and learning material preferences are considered as the two most common and referable learning preferences to understand the learning preferences profile of distance education students. This research investigates the learning preferences of distance education students. Data was collected from 3390 distance education students from Anadolu University, considered as one of the mega universities in the world. Neurol Network Analyze conducted to profile learning preferences of distance education students. For this purpose, Multilayer Perception Model was applied as an artificial neural network analysis model in the analysis of data. The age of students was found as the most important independent variable on the prediction of material preferences and learning technique preferences of distance education students. The full Multilayer Perception Model of the learning preferences profile of distance education students was provided as a conclusion. Recommendations provided for future research and applications.

Keywords: Distance education, learning preferences, artificial neural network.

INTRODUCTION

Distance education gained strong advanced technology support after 20 years of the 21sth century. The technology-oriented nature of distance education has made it stand out in today's rapidly digitalizing societies. Especially, during the social isolation periods of the pandemic process, this unique structure of distance education has ensured the continuation of education at all levels. What makes distance education the rising paradigm is that it is not only technology-oriented but also offers a wide range of instructional materials and learning options.

Studies on personalized learning proposals are critical for the creation of advanced E-learning systems (Zhou, Huang, Hu, Zhu and Tang, 2018). Thanks to the digital transformation of education, it is possible to record and monitor the behavior of individuals in digital environments based on digital data. The transfer of distance education processes to digital has allowed monitoring the behavior of learners who have learning experiences in these environments. In addition to this rich digital data, a completed structure can be reached when data on other learning materials and learning techniques, such as printed resources, are collected. Thus, learners' learning preferences can be profiled more accurately. This creates an opportunity to profile learners' learning preferences and to offer individualized learning environments based on these profiles (Koper, 2015). Profiling and understanding the hidden patterns of learning preferences have critical value in open and distance learning (Rivas, Gonzalez-Briones, Hernandez, Prieto and Chamoso, 2021).

RELATED STUDIES

Artificial Neural Network (ANN) analysis is one of the most appropriate methods to reveal predictive patterns in profiling the learning preferences of distance education students. MLP network is one of the most common and practical architectures of artificial neural networks (Moghadassi, Parvizian, Hosseini, 2009). MLP model is a function of predictor variables that minimizes the prediction bias of the target variables (Heidari, Sobati, vahedirad, 2016). In the related literature, MLP-ANNs have been successfully used to reveal hidden patterns and profile complicated preferences. MLP has been successfully used; in predicting students' academic performance (Oladokun, Adebanjo and Charles-Owaba, 2008), modeling student retention in science and engineering disciplines (Alkhasawneh and Hobson, 2011), and the prediction of student course selection in online higher education institutes (Kardan, Sadeghi, Ghidary and Sani, 2013).

In the research conducted by Yau and Joy (2010), a mobile learning preferences model consisting of 5 dimensions was proposed. These dimensions are; level of motivation, level of distractions, location, time of day, and available time. The model aims to potentially increase the learning efficiency of individuals by matching mobile learning materials appropriate for each student.

As related research, Zhou, Huang, Hu, Zhu and Tang (2018) developed a model of full-path learning recommendation based on clustering and machine learning techniques. A model developed trained based on a feature similarity metric. A series of experiments have been carried out with this model. Results show that recommendations on learning paths significantly improve learning results in terms of accuracy and efficiency.

Veresne Valentinyi and Szalay (2020) investigated the students' preferences for online or printed teaching-learning materials. The findings showed that students use e-learning only to access teaching and learning e-content, and continue to prefer traditional learning methods and resources such as printed materials. In addition, students preferred print and printer-friendly versions of downloadable electronic materials.

In their research, Altinpulluk, Kilinc and Firat (2020) investigated the relationship between lifelong learners' preferences for learning materials and methods according to age, gender, and working status variables. Data was collected from 608 distance education students. Findings revealed that; e-books are not preferred comparing printed books, marking on the book and taking notes was the most preferred learning technique. Additionally, young learners found to study by taking notes and do not prefer to learn by searching on the internet.

Ilin, (2021) investigated how user media preferences influence engagement and motivation in online learning. 122 secondary school students participated in the research. Data were collected through web analytics and user feedback forms. It has been found that behavioral patterns reflect user motivation and learning preferences. The study assumes that these patterns can be utilized to personalize digital content delivery to increase engagement with online learning materials.

The literature on learners' learning preferences is quite rich. Based on previous learning experiences, individual abilities, environment, and interests, learners prefer a particular learning style or a learning way for their learning process (Kolb, 1984; Costa, Souza, Valentim and Castro, 2020). Smith (2001) identified two main learning preference areas in the Canfield Learning Styles Inventory that he developed with university students. The first of these is related to how easily students work with the learning tasks (verbal-non-verbal; collaborative) presented to them. The second is about self-management. Students need a starting place for a better understanding of their own learning process (Gilakjani, 2012). The learner's clear perception of their own learning preferences will allow them to become more independent as learners and play an active role in their own learning (Genovese, 2004; Gilakjani, 2012; Firat, 2021). Similarly, it is possible to reach researches on the use of the MLP model to predict learners' preferences (Oladokun, Adebanjo and Charles-Owaba, 2008; Alkhasawneh and Hobson, 2011; Kardan, Sadeghi, Ghidary and Sani, 2013). However, no study has been found in the literature that analyzes the learning material and learning technique preferences of distance education students with the MLP model. Therefore, it is thought that this research will contribute to filling this gap in the literature.

PURPOSE OF THE STUDY

For the purpose of this study, MLP-ANNs were chosen because they are proven in nonlinear modeling and are resistant to noise and outliers. In this research, the learning preferences of distance education students are considered as learning material preferences and learning technique preferences.

METHOD

This research was designed as a case study. Case study is a methodologically flexible approach to research design that focuses on a specific case (Rosenberg and Yates, 2007). The focused case of this research was active graduate and undergraduate students of Anadolu University Open Education System. Anadolu University, which brings education to different continents of the world with its active-passive approximately 3 million students and 3 million graduates, is among the largest mega universities in the world (AOF, 2017). The education process is fully distance in this system. These features make the students studying in this system a good representative sample of distance education students.

Data Collection Process

Data was collected through an online questionnaire. The questionnaire consists of three parts. The first part includes questions for sex, age, and working status. Second part search to investigate the learning material preferences of distance education students. The question has multiple choices of printed books, digital books, video-animations, visuals-graphics-drawings, audio narration. The final part has a multiple-choice question. This question has eight choices of taking notes, marking in the book, drawing, and scribbling, repeating, telling to someone, listening from others, and discussing with others.

The online survey was published on the system's Web page. Students who wanted to participate by voluntary participation filled out the questionnaire. Students were free to exit the survey at any stage. Data were collected in the fall semester of 2019-2020. 3390 distance education students from Anadolu University Open Education System Programs filled the online questionnaire.

Participants' Profile

The ages of the students participating in the study ranged from 19 to 69. Age distribution of students Is provided in Figure 1.

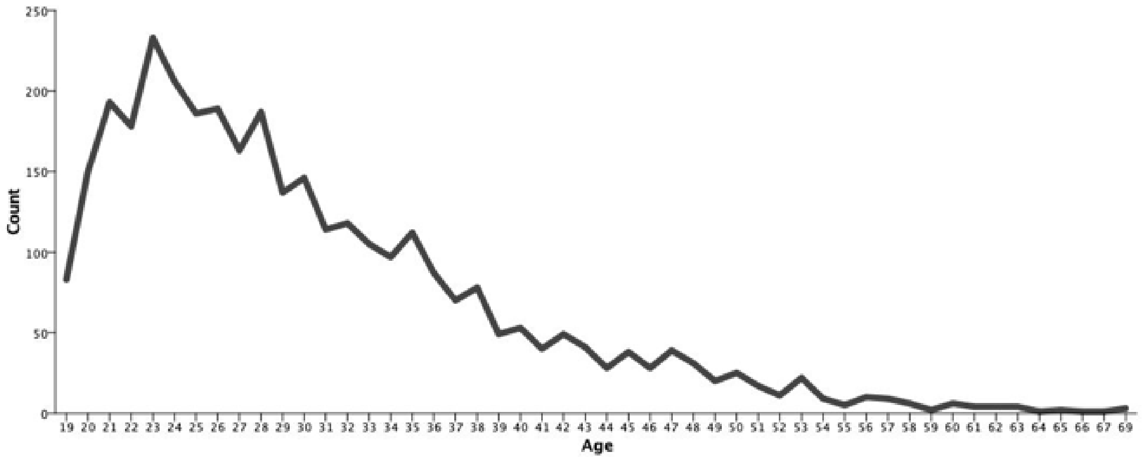

Figure 1. Age distribution of students

42.9% (1455) of the students are female and 57.1% (1935) are male. Another demographic characteristic of the students was their employment status. Statistics of students' employment status are given in Figure 2.

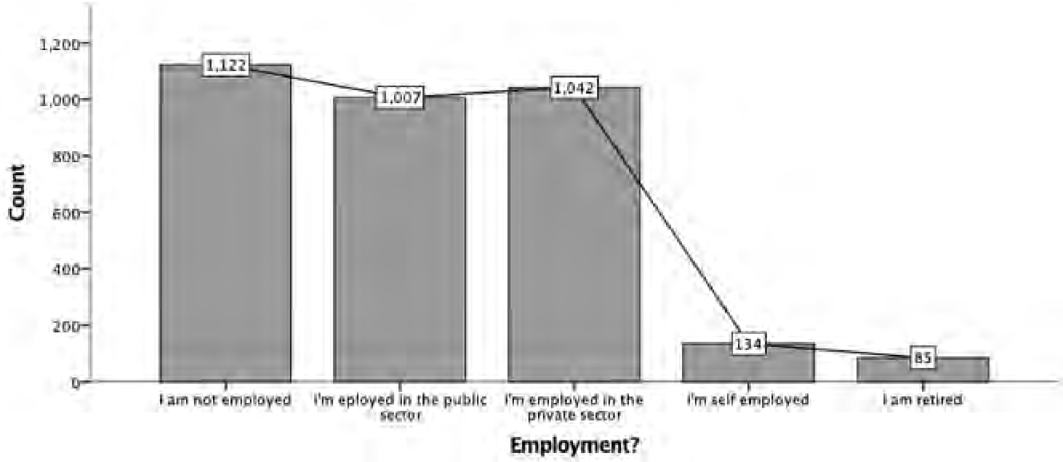

Figure 2. The employment status of students

33.1% of the students who participated in the study stated that they did not work in any job. Then, 30.7% of the students said they work in the private sector, while 29.7% said they work in the public sector. Employment status can be examined in two groups as employed and unemployed. Accordingly, the percentage of students actively working in any job is 64.4%. This data shows that the distance education students in Anadolu University Open Education System have a high rate of employment.

Data Analysis

Classification of data into different clusters or groups is one of the most important aspects in the field of data analyses. The classification of learning experiences can help to understand and identify the hidden paths behind the data. For this reason, neural networks can be used to predict the learning preferences of distance education students based on previous repeats. One of the common neural network models is the multilayer perceptron (MLP) network. MLP network is a common and practical architecture of artificial neural networks (Moghadassi, Parvizian, Hosseini, 2009). MLP is a function of predictors (inputs, independent variables) that minimizes the prediction error (Bias in MLP) of the target variables (outputs, dependent variables) (Heidari, Sobati, vahedirad, 2016). Additionally, MLP has hidden variables that contain unobservable nodes. The value of each hidden unit is a function of the predictors (Rocha, Zela, Torres, Rojas, Valderrama, and Medina, 2021). This structure has a feedforward architecture. In other words, network connections flow one-dimensionally from the input to the output. A typical network architecture for MLP Is provided in Figure 3.

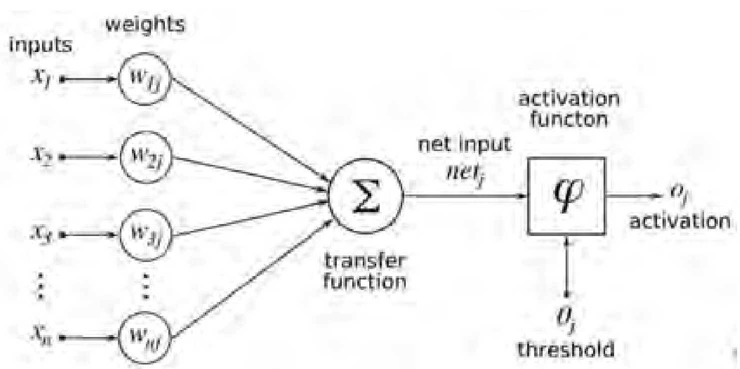

Figure 3. A typical MLP neural network architecture (Najah, 2009)

The pattern of interconnection between neurons in an artificial neural network is called the network architecture (Moghadassi, Parvizian, Hosseini, 2009). The ages of students grouped to 19-29, 30-40, above 40 before applying MLP to collected data. In the MLP analysis, the input variables were age, sex, enrolment status, while output variables were learning material and learning techniques preferences. The artificial neural network analyzes were conducted on IBM SPSS 24 program. The activation function of was Softmax and the error function was Cross-entropy. The hidden layer activation function was Hyperbolic Tangent. The rescaling method for covariates was adjusted normalized.

FINDINGS

MLP generates a predictive model for dependent (target) variables based on the values of the predictor variables. In this research, a predictive model was proposed for learning preferences of distance education students based on age, sex, and enrolment status. Learning materials preferences and learning techniques preferences are the target variables of the model. The MLP artificial neural network model Is applied for learning material preferences and learning techniques preferences separately. Before artificial neural network analysis, the percentages of learning material and learning techniques preferences are provided in accordance with students' independent variables below in Table 1 and Table 2.

Table 1. Percentages of learning material preferences crosstabulation

Independent Variables	Categories	Dependent (Output Variables)				
		Printed Books	e-Books	Visuals-graphics-drawings	Audio narration	Video-animations
Ages	Ages 19-29	50.8%	9.5%	11.9%*	9.5%*	18.3%*
	Ages 30-40	52.1%	12.6%	9.5%	9.3%	16.4%
	Above 40	62.1%*	14.3%*	8.1%	6.1%	9.4%
Gender	Female	58.6%*	7.2%	9.4%	9.8%	15.1%*
	Male	48.3%	14.0%	11.6%	8.4%	17.6%
Employment	I am not employed	57.4%	6.7%	10.2%	8.0%	17.6%*
	I'm employed in the public sector	53.3%	12.1%	10.4%	8.1%	16.0%
	I'm employed in the private sector	45.9%	14.5%*	12.3%*	10.1%	17.3%
	I'm self-employed	49.3%	13.4%	7.5%	16.4%*	13.4%
	I am retired	72.9%*	11.8%	4.7%	7.1%	3.5%

*Note. *The highest percentages of the dependent variables*

As can be seen in Table 1, printed books are the most preferred learning material. Total preference percentages for printed books are 52.7%, Video-animations 16.5%, e-Books 11.1%, Visual 10.7%, Audio narration 9%. Learning techniques preferences percentages of students are provided in Table 2. This finding shows that the most preferred materials are printed books and video animations. These two material types represent the two sides of digital and print learning materials.

Table 2. Percentage table of learning techniques preferences crosstabulation

Independent Variables	Categories	Dependent (Output Variables) Discussing with others	Listening from others	Teaching someone	Drawing and scribbling	Taking notes	Searching on the Internet	Marking in the book	Repeating
Ages	Ages 19-29	9.2%*	7.7%*	13.8%*	7.1%	29.3%*	2.7%	20.6%	9.6%
	Ages 30-40	6.7%	7.7%*	8.1%	11.5%*	24.3%	3.9%*	26.0%	11.9%
	Above 40	1.8%	3.7%	5.5%	10.7%	21.5%	2.9%	35.1%*	18.9%*
Gender	Female	5.2%	6.9%	12.8%*	8.0%	32.4%*	1.2%	24.6%*	8.9%
	Male	9.1%*	7.3%*	9.6%	9.7%*	22.5%	4.5%*	23.9%	13.5%*
Employment	I am not employed	7.8%	7.8%	12.7%*	7.0%	29.9%	2.9%	22.2%	9.7%
	I'm employed in the public sector	7.1%	5.9%	8.8%	11.2%	19.9%	3.8%	29.9%	13.4%
	I'm employed in the private sector	7.4%	8.2%*	12.2%	8.8%	30.5%*	2.6%	19.8%	10.6%
	I'm self-employed	9.7%*	7.5%	6.0%	9.0%	26.9%	4.5%	23.9%	12.7%
	I am retired	2.4%	1.2%	5.9%	9.4%*	20.0%	1.2%	37.6%*	22.4%*

Note. **The highest percentages of the dependent variables*

These descriptive cross-tabs are provided before the MLP model to understand the highlights of the data. Table 2 shows that marking in the book and taking notes are the most preferred learning techniques. Total preference percentages for Taking Notes are 26.8%, Marking in the Book 24.2%, Repeating 11.5%, Teaching Someone 10.9%, Drawing and Scribbling 8.9%, Discussing with Others 7.4%, Listening from Others 7.1% and Searching on the Internet 3.1%. Table 2 shows that taking notes and marking in the book are the most preferred learning techniques by distance education students.

Learning Material Preferences

The number of training cases was 2361 (69.6%) and the number of testing cases was 1029 (30.4%). The percent incorrect predictions for the training step was 47.5%, for the testing step was 46.7%. This means that the accuracy of the model is over 52% for the model. The synaptic network of the model Is provided in Figure 4.

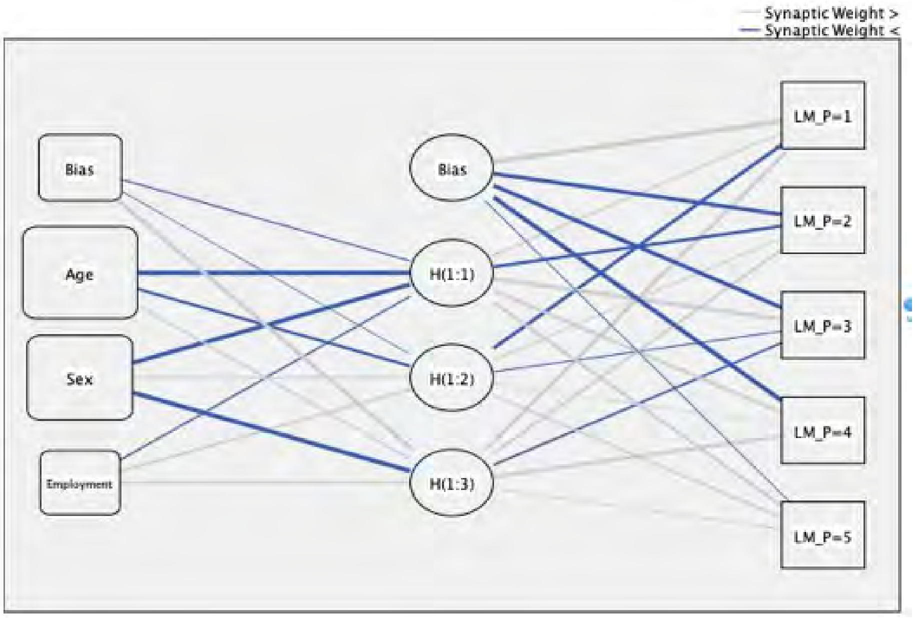

Figure 4. MLP synaptic weights for learning material preferences

Synaptic weight refers to the strength of a connection between two nodes (Byrne, 2017). In biology, it refers to the amount of influence one neuron has on the firing of another. The term is used in artificial and biological neural network research. In the Figure 1, gray connections indicates positive impacts (synaptic weight > 0), blue connections indicates negative impacts (synaptic weight < 0) on the output layer (dependent variable). The overall percent of the accuracy of the classification found 52.1% for the testing step and 53% for the training step. The parameter estimates are provided in Table 3.

Table 3. Parameter estimates for learning material preferences

Predictor	Predicted								
	Hidden Layer			Output Layer					
	H(1:1)	H(1:2)	H(1:3)	[LM_P=1] Books	[LM_P=2] e-Books	[LM_P=3] Visuals	[LM_P=4] Audio	[LM_P=5] Video	
Input Layer	Age	-.720	-.314	.197					
	Sex	-.496	.180	-.602					
	Employment	-.171	.250	.267					
Hidden Layer	H(1:1)				.199	-.363	.467	.348	.375
	H(1:2)				-.406	.147	-.086	.026	.206
	H(1:3)				.453	.301	-.202	.386	.074

The importance of independent variables on the prediction of output variables gives important ideas to understand the neural network. The normalized importance of age was .434, sex was .370 and employment was .196. Normalized importance is simply the importance values divided by the largest importance values and expressed as percentages (IBM, 2021). This means that age has been identified as the most important variable in the estimation of preference of learning materials. The synaptic network of sub-categories Is provided in Figure 5.

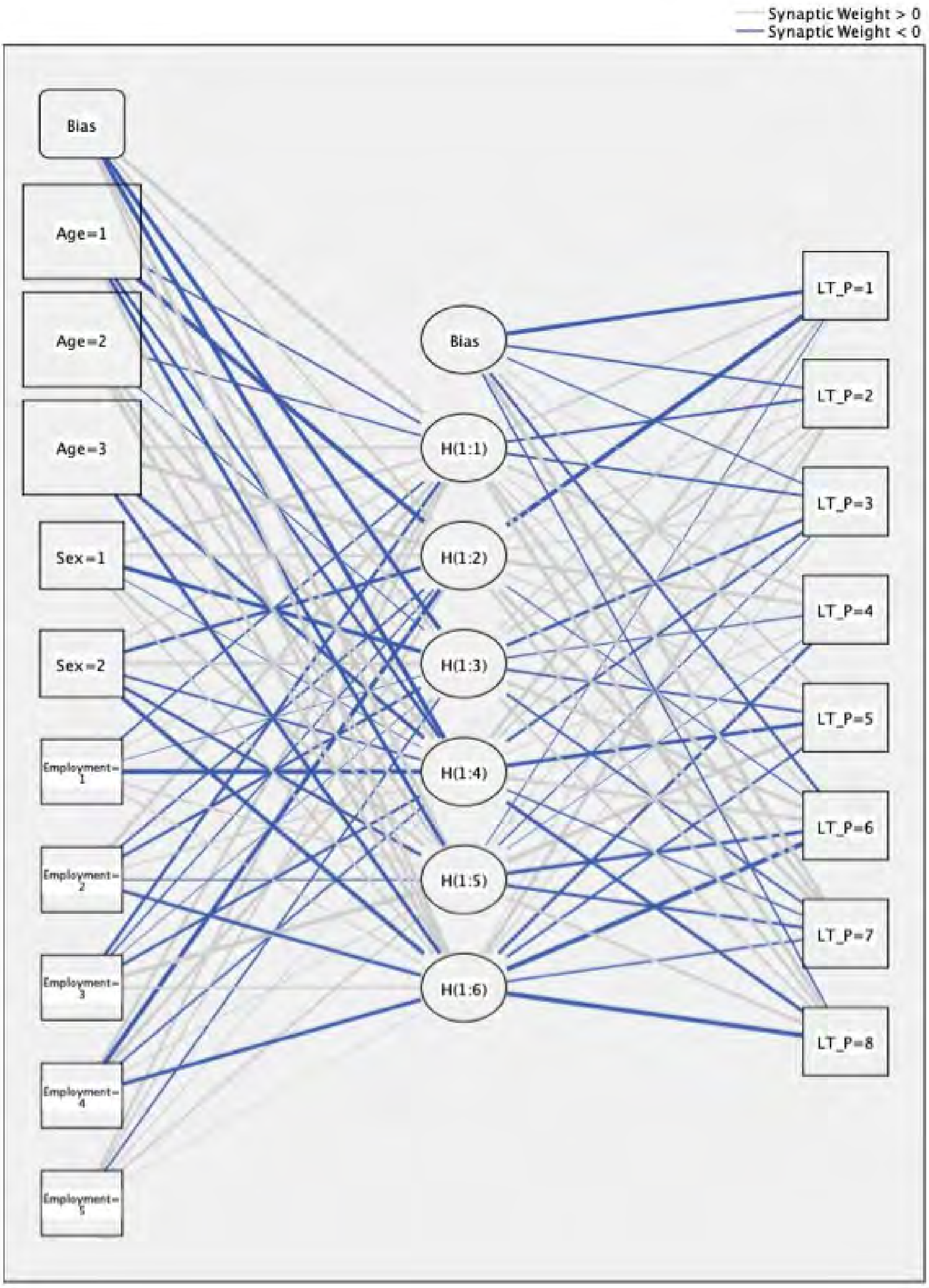

Figure 5. MLP synaptic weights for learning techniques preferences

Learning Techniques Preferences

The number of training cases was 2339 (69.0%) and the number of testing cases was 1051 (31.0%) for MLP artificial neural network analysis. The training had 71.8% incorrect predictions percent while the testing step had 69.9%. The synaptic network of the model Is provided in Figure 6.

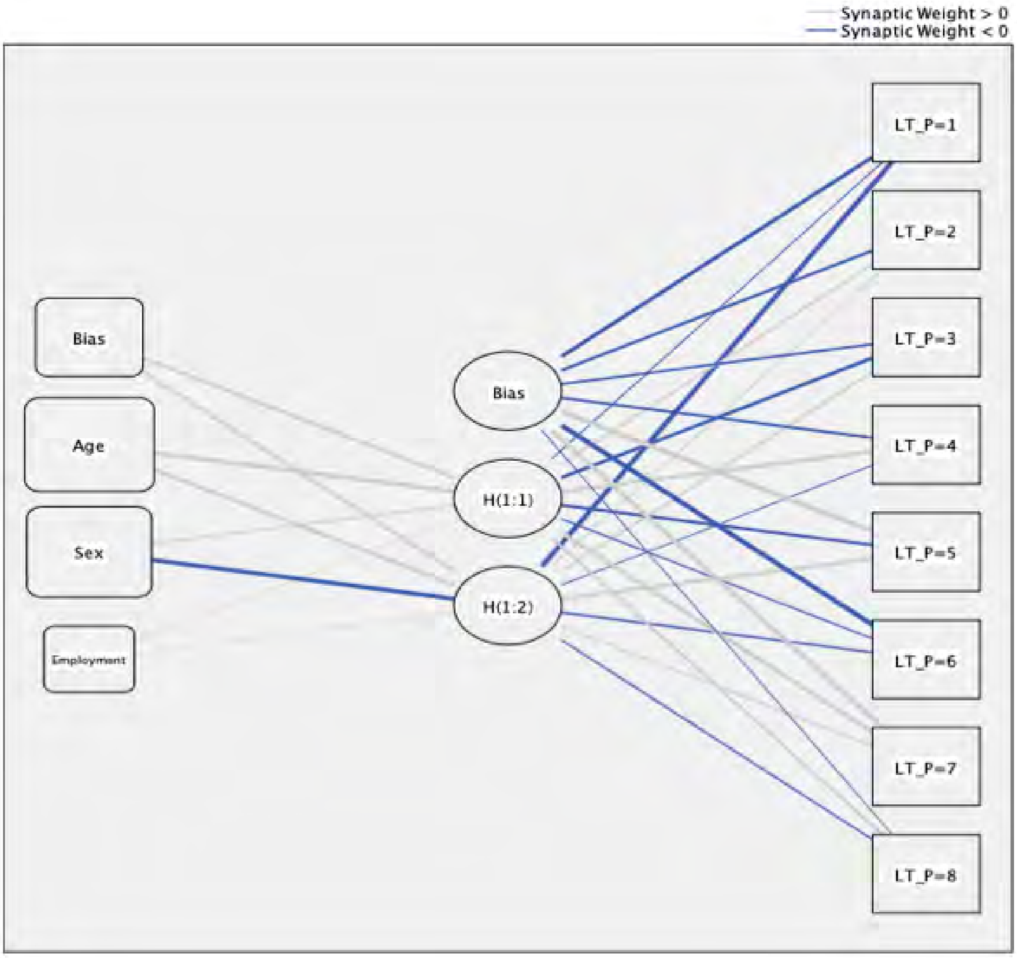

Figure 6. MLP synaptic weights for learning technique preferences

The normalized importance of age was .5, sex was .447 and employment was .054. Age has been identified as the most important variable in the estimation of learning techniques preferences. The normalized importance of gender was close to ages for learning technique preferences. It is possible to assume that both age and gender are important independent variables to predict the learning technique preferences of distance education students.

Learning Material and Learning Technique Preferences

The third MLP analysis was applied to investigate a predictive relation between learning material preferences and learning technique preferences. In the MLP artificial neural network analysis, the number of training cases was 2353 (69.4%) and the number of testing cases was 10537 (30.6%). The training step had 68.4% and the testing step had 69.3% incorrect predictions percent. The synaptic network of the model Is provided in Figure 7.

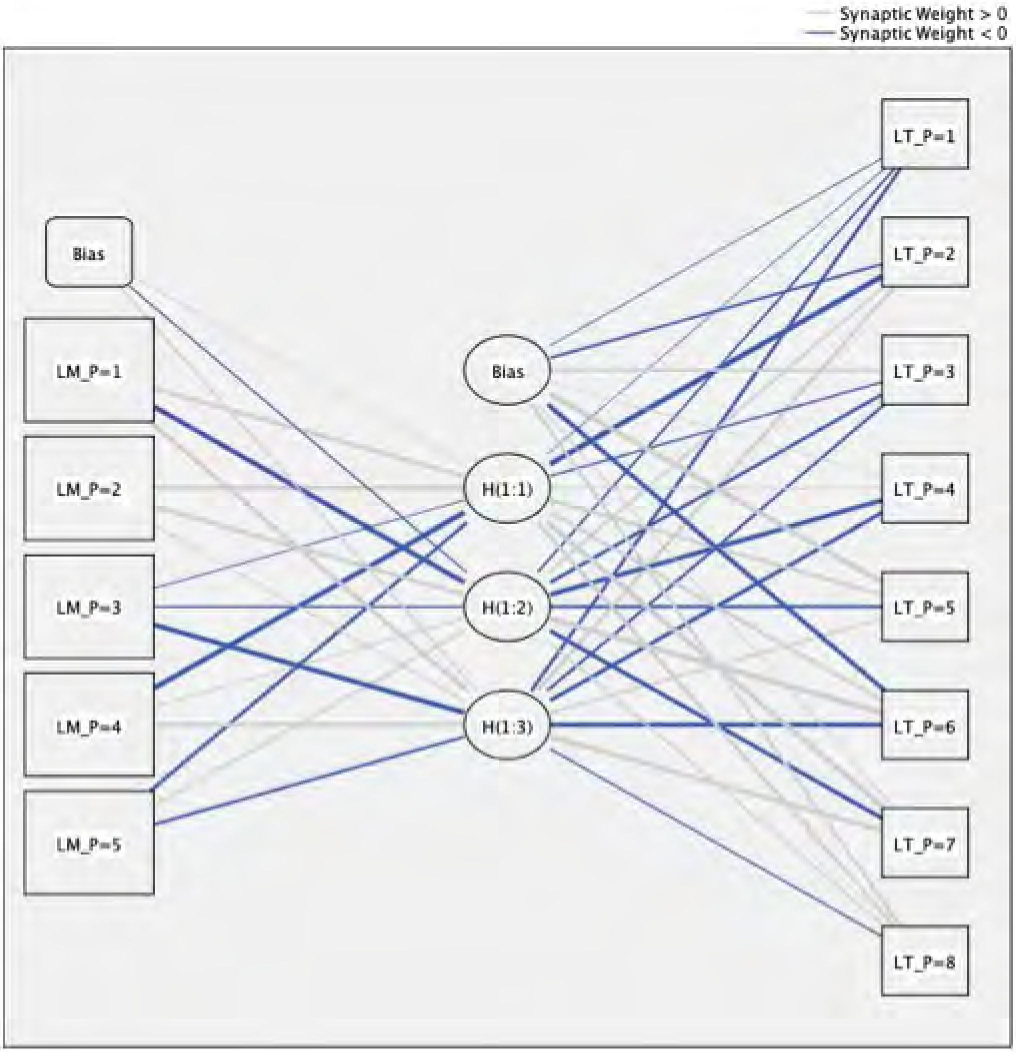

Figure 7. MLP synaptic weights for learning material and learning technique preferences

A high number of strong estimates and synaptic weights were observed between learning material preferences and hidden variables; hidden variables and learning technique preferences. The predictive stats are provided in two tables. The first table of this MLP analyzes created for input layers and hidden layers.

Table 4. Input layers and hidden layers estimates

Predictor		Predicted		
		Hidden Layer		
	H(1:1)	H(1:2)	H(1:3)	
Input Layer	[LM_P=1]	.531	-.986	.788
	[LM_P=2]	.814	.667	.095
	[LM_P=3]	-.042	-.140	-.944
	[LM_P=4]	-1.014	.107	.659
	[LM_P=5]	-.430	.245	-.339

The second table of MLP neural network analysis was created for hidden layers and output layers. This table is provided in Table 5.

Table 5. Hidden layers and output layers estimates

Predictor	Predicted									
	Output Layer									
	[LT_P=1]	[LT_P=2]	[LT_P=3]	[LT_P=4]	[LT_P=5]	[LT_P=6]	[LT_P=7]	[LT_P=8]		
Hidden Layer	H(1:1)	.322	1.077	.357	-.362	.024	.385	-.718	.236	
	H(1:2)	-.363	-.568	-.134	.230	.160	-.085	-.404	.138	
	H(1:3)	-.444	-.697	-.468	.057	-.100	.500	-.011	-.026	

DISCUSSIONS AND CONCLUSION

The purpose of this research was to profile the learning preferences of distance education students with the help of artificial neural network analysis. For this purpose, the MLP model was applied to data collected from 3390 distance education students from Anadolu University Open Education System. The descriptive findings show that printed books and video animations are the most preferred learning materials. This finding supports the similar findings of Veresne Valentinyi and Szalay (2020) and shows that the habit of using printed materials is still strong in distance education students. However, the second most preferred video animation shows that a digital transformation has occurred in material selection. The second important descriptive finding was that taking notes and marking in the book are the most preferred learning techniques by distance education students. These two descriptive findings of this research support the finding of Altinpulluk, Kilinc and Firat (2020) on the highest preference of printed books and taking notes.

Combined learning preference profile model of distance education students produced with the help of MLP ANN model. MLP model applied three times for independent variables and learning material preferences, independent variables and learning preferences variables, learning material preferences, and learning techniques preferences. The findings of these three MLP analyzes integrated to design the overall profile. The visual model of the overall profile model of the learning preferences of distance education students Is provided in Figure 8.

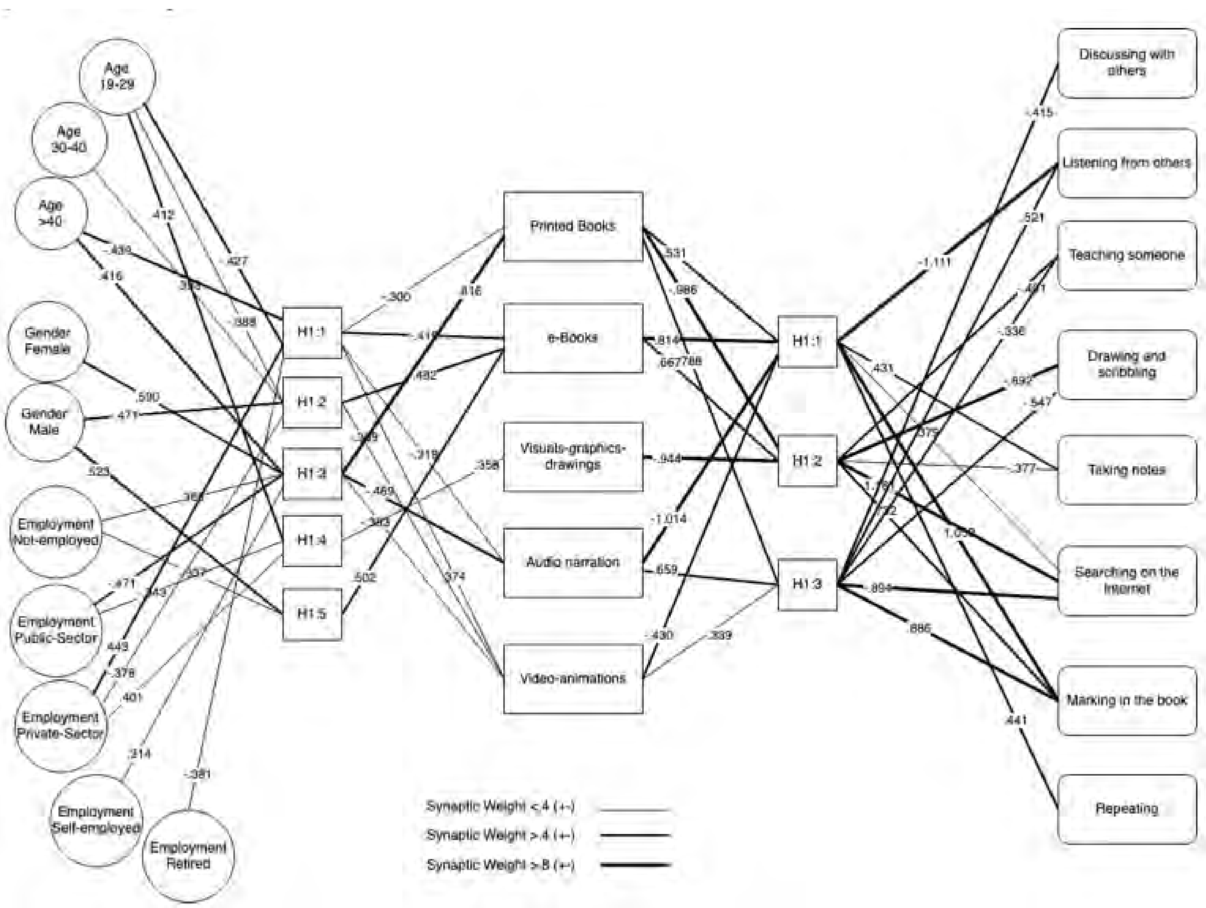

Figure 8. Overall profile model of the learning preferences of distance education students

Bias removed from the final overall model. Level of synaptic weights illustrated with the thickness of the line. The overall model covers the network of all input variables, hidden variables, and output variables. The high estimated learning preferences paths are listed below:

- Students with ages between 19-29 tend to use e-books and visual material and prefer to listen to others, drawing-scribbling, and search on the internet.
- Students aged over 40 tend to use books (printed and e-book) and audio narrations as materials and prefer marking in the books and listening from others for learning.
- Female students prefer printed books and audio materials, while Male students prefer e-books, video-animations. Both female and male students prefer listening from others, marking in the book, and taking notes.
- Employed students from public sectors tend to prefer printed books and audio materials, while students from the private sector tend to prefer e-books and visuals. Employed students from public sectors tend to prefer listening from others, marking in the book, and taking notes, while students from the private sector tend to prefer listening from others, marking in the book, taking notes, drawing, and searching on the internet.

Based on this ANN model, the learning preferences of distance education students can be estimated for each demographic feature. Thus, designing personal learning environments estimation and recommendations of further interactions in e-learning environments became more possible. Such recommendations based on learning paths can significantly improve learning results as found by Zhou, Huang, Hu, Zhu, and Tang (2018), increase engagement as found by Ilin (2021). The full model of an artificial neural network can be used to estimate the potential use of learning materials and preferred learning techniques. Based on this understanding, instructional designers, content developers, interactors, Web development teams and even administration of the distance education system can develop strategies and plans for further actions.

In future research, ANNs can be used to understand the predictive learning preference profiles of students in e-learning environments with the extended number of participants and variety of demographic information. Additionally, ANN results can be supported with learning analytics of students in the e-learning environments and their views about the network.

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