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Factors Affecting Vocational College Instructors' Usage of LMS in the Post-Pandemic Normal

Umut Birkan Özkan, Assoc. Prof. Dr., National Defence University, Türkiye, umutbirkanozkan@gmail.com
0000-0001-8978-3213

Harun Çiğdem, Assoc. Prof. Dr., National Defence University, Türkiye, hcigdem@gmail.com
0000-0001-5958-5216

Gökhan Yarar, PhD., Türkiye, gokhanhocam@hotmail.com
0000-0002-0339-3773

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Abstract

The use of a learning management system (LMS) in education is becoming more and more appealing. This study aimed to look at the variables influencing Turkish vocational college instructors' behavioral intentions (BI) in using the college's LMS, called the Course Portal (CP), following the pandemic. The LMS factors of self-efficacy (SE), area of scientific expertise (ASE), and interactivity (INT) are used in this extended Unified Theory of Acceptance and Use of Technology (UTAUT) model. A total of 105 instructors completed an online questionnaire. The regression model and artificial neural network approaches were used to analyze the data. The findings demonstrated that the instructors' BI in using the CP could be anticipated from the SE and instructors' ASE, and the instructors' behavior in the use of the CP could be anticipated from facilitating conditions (FC), INT, and the BI to use it. Performance expectancy (PE), effort expectancy (EE), and social influence (SI) were ultimately excluded from the final model due to their insignificant connections with BI. It is suggested that instructors' BI to use the CP will be high if their scientific expertise coincides with the e-learning and that instructors' BI to use e-learning will also grow, in their opinion, as their SE increases. Nevertheless, it is reasonable to conclude that instructors' BI, including the availability of FCs and an interactive LMS, will boost their overall use of LMS.

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INTRODUCTION

E-learning programs, notably a learning management system (LMS) that depicts web-based learning processes, now dominates many educational applications. Modern technology has played a vital part in helping instructors teach learners from afar by leveraging a variety of digital platforms and tools as teachers have been drawn to online education (Zacharis & Nikolopoulou, 2022). Since it provides convenience and flexibility to both instructors and students, the LMS has had a revolutionary impact on education and has become an enticing as well as a widespread education alternative. An LMS is a robust online content process that supports learning and teaching activities and is an extensively employed application in higher education (Lavidas et al., 2022). It is also an impressive tool since it allows the use of new online educational resources in teaching and learning that are typically not possible in traditional courses. The LMS has become the standard flat form for a modern educational organization, covering schooling announcements, lecture presentations, test revisions, report submissions, online assignment submissions, and course registration (Nguyen, 2021). The purposes of using an LMS in organizations are threefold: to develop their instructional systems, to fulfill the demands of their students, and to prepare the next generation for future questions (Hernandez et al., 2011). Given the usage rate of 99% in higher education institutes, LMS technology is the most widely used innovation in e-learning software. LMS, which has become increasingly widespread in recent years, was initially designed to manage distance education. However, supporting traditional in-class learning in mixed learning has become increasingly important as time has passed. Therefore, the use of an LMS may be considered a significant instructional technology used by a wide range of educational institutions at all levels, particularly in higher education (Cheng & Yuen, 2018). LMSs are feature-rich systems that are used to encourage both online and traditional classroom learning (Islam, 2013). LMS offers the infrastructure that authorizes instructors to develop and present course materials, track students' progress, communicate with them, and provide online learning experiences (McGill & Klobas, 2009). In addition, the LMS acts as a link between instructors and other instructional tools (Sinclair & Aho, 2018). Lecturers may offer a variety of learning experiences (video, lecture notes, lecture presentations, discussion forums, online homework, online tests, etc.) to their students using the LMS, and students can access the prepared content without time or space limitations.

An LMS technology is used in higher educational institutions, through mandatory practice or with departments making their own decision regarding its use It is pivotal to use the LMS successfully in educational activities to complete the course of study expectations of today's students and to provide a variety of learning objectives. However, institutional investment in an LMS does not guarantee that instructors will develop content for the LMS or that the LMS will be effective. Furthermore, academics' adoption and utilization rate of the LMS may often be lower than institutional expectations (Teo, 2012). In addition, one of the major factors that may hinder LMS acceptability by instructors is the institutions' absence of an LMS utilization strategy (Wrycza & Kuciapski, 2018).

Aside from the fact that LMS usage has increased rapidly over the last decade, the COVID-19 pandemic that broke out on March 11th, 2020, demonstrated that educational institutions still face challenges in using e-learning applications. A significant roadblock to efficient LMS adoption is a lack of interest among teaching staff Instructors' features, students' features, the technology used, and the assistance available are four significant features that influence the LMS application's performance (Selim, 2007). Determining the factors affecting a new technology's acceptance and use is an important research topic in studies because potential individuals must first understand and accept the technology before expanding the use of technological breakthroughs (Teo et al., 2019; Wrycza & Kuciapski, 2018). LMS technology progresses and lecturers use it in their professional lives; instructional technology researchers are still trying to understand what variables influence the instructors' use of this technology. The most important motivation for this research subject is that the benefits of LMS cannot be fully maximized unless instructors and students adopt the LMS (Teo, 2012).

All the suggestions mentioned above indicate that, in developing viable solutions, attention should be paid to understanding the instructors' BIs and use of the LMS. As a result, finding the crucial characteristics that influence instructors' use behavior and their BIs in using an LMS continues to be a major challenge.

THEORETICAL BACKGROUND

The user's BI, inspired by the user's expectations, usually influences how new technology is used (Fishbein & Ajzen, 1975). Numerous theoretical models that investigate the acceptance of the information system employ the concept of BI to identify factors that affect user utilization, guiding the best information system implementation and design. Numerous theoretical models based on technology have been created to explain how people perceive and accept new information technologies (Razkane et al., 2022). Two theories and models that describe how people adopt new technology are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis et al., 1989). On the other side, The UTAUT model was established to describe a technology's user acceptance. It becomes clear that all models follow a similar process for accepting an innovation if their structure is analyzed (Venkatesh et al., 2003). This cycle happens as the person experiences favorable responses to adopting innovation, good behavior intents for use, and then uses the innovation.

Compared to other models, the UTAUT model (Venkatesh et al. (2003), was developed specifically for assessing an innovation's acceptance and use. Also, it provided a broad opportunity to understand information system acceptance and was used to identify the variables influencing instructors' BI to use and use behavior of LMS. UTAUT is an outstanding model and one of the most utilized frameworks in this context. The UTAUT model was suggested by Venkatesh et al. (2003), and they reported that the model was influenced by four significant independent variables and four moderators of information systems usage behaviors. Gender, age, experience, and volunteering are our moderators, while PE, EE, SI, and FC are independent variables. According to the model, these variables have an impact on an individual's BI.

Unique ideas about a system that rewards employees for their work performance are referred to as PE (Venkatesh et al., 2003). PE in instructional technology indicates working performance (Khechine et al., 2020), and in this regard, people choose to adopt programs that they feel will increase their company performance. The promise of improving performance via LM S will increase the willingness to utilize LMS. The instructors will be more eager to utilize the LMS if it is effective and helps them improve their work performance. One of the most common positive predictors of individuals' BI is PE (Venkatesh et al., 2003).

The degree of simplification in technology utilization is commonly referred to as EE. This factor indicates that instructors find LMS easy to use in the context of instructional technology. Lecturers will be more interested in using this innovation if it is simple and requires little effort. The expected effort, like expected performance, is frequently discovered to be a significant factor of BI (Venkatesh et al., 2016).

SI measures how many others value technology use (Venkatesh et al., 2003). SI represents the opinions of other instructors regarding the use of LMS when it comes to the topic. Although Mtebe and Raisamo (2014), reported that SI on BI use had no significant effect, numerous research has found SI to be one of the significant predictors of BI (Khechine et al., 2020). On the other hand, Hartwick and Barki (1994) suggest that SI is more prominent when it is needed. Because they use new technology daily, mandatory users appear to place greater weight on others' ideas, whereas volunteers do not emphasize others' ideas (Hartwick & Barki, 1994).

The third variable, the notion that a person would receive organizational or technological infrastructure help in the innovation process, is referred to as FCs (Venkatesh et al., 2003). Human and technical supports are FCs in terms of instructional technology for using LMS. When instructors perceive that network infrastructure is sufficient for LMS use and, in some cases, they have an office to call, they are expected to be more willing to utilize LMS. As a result, teachers with a lot of support and good infrastructure are more likely to use LMS effectively. UTAUT2 significantly impacts e-learning technology adoption research (Lahrash et al., 2021). According to the UTAUT2 model, FCs and BI have a significant positive link (Venkatesh et al., 2016).

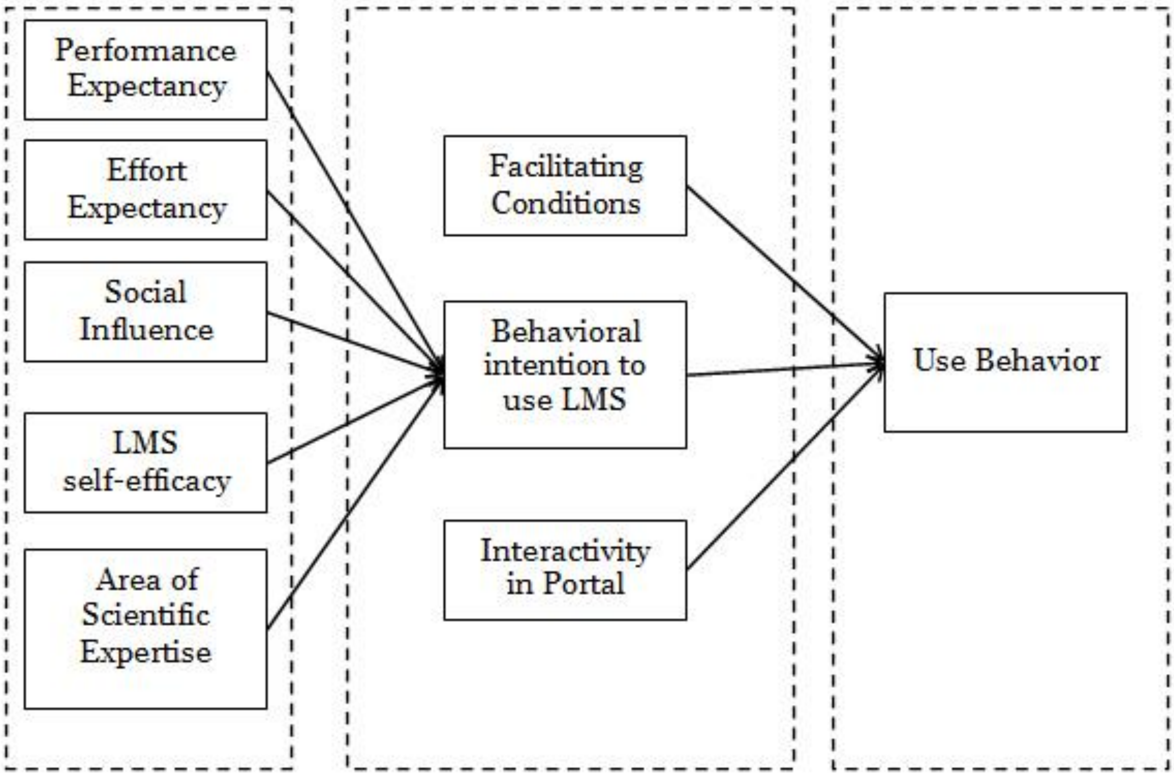
BI, as a dependent variable, explains people's intentions to utilize new technology in the future (Davis, 1989; Warshaw & Davis, 1985), whereas usage behavior refers to how much they use new technology. This refers to the instructors' aim to use the LMS in the context of instructional technology. The BI to use technology is often related to and required for the use of associated technology, according to most technology acceptance models. In this example, the classic UTAUT model was chosen as the basic model because it is a viable alternative to other theoretical acceptance models. UTAUT model recognizes these factors, including PE, EE, and SI, have a direct effect on BI use and FCs, and BI use directly affect the use behavior (Venkatesh et al., 2003). Furthermore, moderators such as gender, age, experience, and volunteering can alter the influence of BI predictors in the model (Venkatesh & Zhang, 2010). Recent studies have found that, in addition to the required criteria in UTAUT, many other factors can fully anticipate an information system's use behavior and provide a deeper understanding. Many researchers have modified the classic form of the UTAUT by adding other variables and factors or by eliminating existing ones. This present study employed the factors suggested by Wrycza and Kuciapski (2018) and the model generated by adding LMS SE to UTAUT.

Using LMS is identical to using any other information system, but several context-specific factors may also affect the intention to use it. For this reason, the instructors' motivation to use LMS may differ significantly from that of other systems. Instructors may expect not just to enhance performance, reduce efforts, or increase social status but also for the LMS to be specialized to their field, interactive, and capable of being used by themselves. Many researchers have confirmed the UTAUT model as a sound model in various areas; however, it does have certain limitations. For example, while earlier studies have revealed that perceived SE has a considerable and positive effect on an individual's motivation and performance (Bandura, 1977), in the UTAUT model, SE does not appear to be a powerful determinant of BI. This study adds the SE factor to the research model to determine the teachers' perceptions of LMS performances. Thus, if the instructors realize that utilizing LMS surpasses their abilities and skills, we may assume that they will avoid using LMS, according to this study. Users who have a higher level of LMS SE are more likely to engage in LMS-related activities (Baki et al., 2018; Hsia et al., 2012); for example, SE, according to Ong and Lai (2006), influences both the need to apply e-learning and its performance.

Another significant factor for all learning environments is INT, regardless of the teaching technique or technology employed (Moore & Kearsley, 2011). It can be a critical aspect in developing instructors' good attitudes toward LMS (Wrycza & Kuciapski, 2018). All these factors show that an LMS's INT should be a key factor affecting instructors' decision to use it or not (Wrycza & Kuciapski, 2018). Because this feature of the LMS has not been commonly given to instructors in prior practices, it is expected to promote LMS usage. Another independent variable is the instructors' ASE, which stems from the fact that the study spans all departments of a military vocational school. Instructors in departments like Computer Technology utilize ICT technology in their everyday life and scientific studies, whereas instructors in other departments may be unfamiliar with e-learning since LMS is a different teaching technology than presentation preparation applications. For this reason, lecturers might request additional courses to learn about online teaching. ASE is generally identified as the extent of a belief that using LMS fits and develops its science teaching field (Wrycza & Kuciapski, 2018).

Herein, LMS SE and ASE are considered determinants of research design for instructors, while environmental factors focus on FCs and INT in LMS. The study intends to conduct an extended UTAUT model to explore the association between instructor's use behavior of the LMS and selected factors such as PE, EE, SI, LMSSE, ASE, BI, FCs, and INT in LMS (see Figure 1). Given that FCs and INT in LMS are connected to the development of LMS and would affect use behavior rather than BI to use LMS, we decided to add these variables into use behavior.

Figure 1. *Extended UTAUT framework of the study*



The model is conceptualized in the following way: BI to use LMS may be influenced by PE, EE, and SI from the UTAUT model, and LMS-SE, as well as ASE, is discussed in the first section. In a similar layer, the second section covers BI to use LMS, FCs, and INT in LMS, which tends to positively affect the use behavior that we discussed in the last section. The UTAUT of Venkatesh et al. (2003) serves as the conceptual underpinning for the present study. Also, other factors such as the ASE and INT in LMS as suggested by Wrycza and Kuciapski (2018) have been incorporated into the model, allowing it to achieve a unified conceptual framework. Understanding the instructors' LMS use behavior is a crucial topic based on the design discussed so far, not only to increase the use of the LMS but also to demonstrate its potential effects. With that in mind, the purpose of this research, which was based on Wrycza and Kuciapski (2018) extended UTAUT model, was to examine the determinants affecting military vocational college instructors' BI to use the LMS and its constructing factors, including PE, EE, SI, LMSSE, ASE as well as its predictors, FCs and INT in LMS at a post-secondary vocational college.

Other LMS researchers and providers will gain a comprehensive understanding of instructors' use behavior and BIs concerning the use of LMS through this study's findings. Consequently, they can plan and offer better LMSs that will enable more instructors to use and produce more efficient results. The development of LMS has made it simpler to create interactive lessons, and the interaction between instructors and students has increased. Therefore, looking into the impact of LMS INT on instructors' LMS use behavior has become critical. For the current study, the institution where the research is conducted is also critical. Because the internet access accessible to students in the military vocational college where the research is undertaken is limited, it is deemed necessary that the LMS be enhanced and utilized by the instructors. Hence, using LMS in such environments is a valuable opportunity to influence instructors positively and increase their engagement.

Moreover, the fact that most of the instructors in the military vocational college where the research was done are brand new to their jobs and are not teacher-based makes this study relevant. Much research has been done on higher education; however, relatively little research has been conducted on post-secondary military vocational schools. So, this study with two-year post-secondary military vocational school instructors intends to contribute to the literature by presenting examples of similar educational environments.

Institutions make significant investments to incentivize the use of LMS, and it is essential to determine the factors affecting instructor LMS use in the post-COVID period. Previous studies include several specific external factors (TAM, UTAUT, UTAUT2) that cover part of the behavioral intentions of instructors to use the LMS, as is evident from the literature review. This study tries to provide a completer and more accurate picture by integrating many of the previously mentioned criteria as well as new factors (Interactivity, Facilitating Conditions) that have emerged with the advancement of technology. Most of the literature on LMS centers on higher education institutions with advanced LMS infrastructure and lecturers that use LMS effectively (Al-Fraihat et al., 2020). Although most studies were conducted in universities, the factors influencing instructors' intentions to use LMS in some schools were not investigated. In less researched colleges, such as post-secondary military vocational schools, less is known regarding instructors' LMS usage. As a result, the primary goal of this research is to look into the LMS usage patterns of two-year post-secondary military vocational school instructors, as well as the factors that may influence this behavior in the post-pandemic normal. by understanding the elements that drive LMS use behavior, instructors and institutions can determine what steps they may take to increase LMS use.

The following are some of the research questions that this study aims to investigate:

-Can BI to use LMS be predicted by PE, EE, SI, LMSSE, and ASE?
-Can use behavior be predicted by BI to use LMS, FCs, and INT features of the LMS?

METHOD

A quantitative research design of the relational survey type was adopted to achieve the study's goals. This study was conducted urgently after the successive lockdowns in a military vocational college. Because researchers are instructors, convenience sampling was used to select the participants. One of the researchers revised the LMS, which was named "Course Portal" and was developed using MOODLE, and its new version was introduced in the 2021-2022 academic year. Because of the school's unique situation, the LMS only broadcasts on the intranet, with no external access. At the start of the 2021-2022 academic year, an LMS manager was appointed to each department, and the researcher provided training about how to use the LMS properly. Department administrators provided the appropriate information to their departments, and all courses were made available on the LMS. On the other hand, instructors were not obliged to utilize the LMS.

PARTICIPANTS

This study included 105 instructors who used LMS during the 2021-2022 academic year. It was entirely voluntary to take part in the survey. The demographic information of the 105 faculty members that participated in the study is shown in Table 1.

Table 1. *Personal Characteristics of Instructors*

Gender	*n*	*%*
Male	87	82.85
Female	18	17.15
Age		
20-24	14	13.33
25-29	50	47.62
30-34	10	9.52
35-39	12	11.43
40-44	10	9.52
45-49	8	7.62
50-55	1	0.96
Department		
Technical Departments	55	52.38
Non-Technical Departments	50	47.62
Graduation		
Not Teacher Based	68	64.76
Teacher Based	37	35.24

Instructors, especially those who are not teacher-based graduates, do not have any LMS experience. It is also worth noting that the institution where the research was conducted is a newly established university and most of the participants are under the age of 30 and had their first teaching experience here. In addition, MOODLE, a free software, was used as the LMS, and a four-hour training was given to the instructors in all departments at the beginning of the semester on the use of LMS and its features (file upload, exam creation, homework, etc.).

DATA COLLECTION INSTRUMENT

The information was gathered in Turkish utilizing an online 5-point Likert-type scale questionnaire with a response range of 5 (strongly agree) to 1 (strongly disagree) adapted from Wrycza and Kuciapski (2018) expanded UTAUT model. LMS self-efficacy factor from Zheng et al. (2018) was added to the questionnaire. The questionnaire, which took 15 minutes to complete and comprised 30 items and a separate section with questions about the participants' demographic characteristics, was designed to meet the study's objectives.

Aside from the demographics, the questionnaire had eight subscales that represented instructors' LMSSE, PE, EE, SI, FCs, System INT of the LMS, instructors' ASE, and BI to use the LMS and use behavior. The items on each subscale are listed in Table 2.

Table 2. *Items Placed on Each Subscale*

Subscales	*Items*	*Mean*	*SD*
*Performance Expectancy**			
I1	I find LMS useful in teaching.	4.30	.89
I2	Using LMS enables me to accomplish teaching activities more quickly.	4.13	1.00
I3	Using LMS increases my teaching productivity.	4.02	1.01
I4	If I use LMS, I will increase my chances of getting a positive evaluation.	3.73	1.02
*Effort Expectancy**			
I5	My interactions with LMS have been clear and understandable.	4.01	1.03
I6	It is easy for me to become skillful at using LMS.	4.18	.95
I7	I find LMS flexible and easy to use.	4.09	1.01
I8	Learning to operate LMS does not require much effort.	4.17	.90
*Social Influence**			
I9	I find LMS useful in teaching.	4.30	.89
I10	Using LMS enables me to accomplish teaching activities more quickly.	4.13	1.00
I11	Using LMS increases my teaching productivity.	4.02	1.01
*Facilitating Conditions**			
I12	I have the resources necessary to use LMS.	4.00	.99
I13	I have the knowledge necessary to use LMS.	4.22	.80
I14	A specific person (or group) is available for assistance with LMS difficulties.	4.22	.90
I15	My computer is compatible with and able to support LMS.	4.25	1.02
*Interactivity in LMS***			
I16	LMS enables interactive communication between teacher and students.	4.00	.92
I17	LMS enables interactive communication among students.	3.77	1.01
I18	Communication opportunities in LMS are effective (e-mail, bulletin board, online chat, etc.)	3.54	1.07
*Area of Scientific Expertise***			
I19	My area of scientific expertise is convenient for teaching with LMS.	4.06	.88
I20	LMS has sufficient tools to teach my area of scientific expertise.	3.94	.95
I21	LMS makes easier to teach my area of scientific expertise.	4.05	.88
*Behavioral Intention**			
I22	I intend to use LMS in the future.	4.23	.91
I23	I predict I would use LMS in the future.	4.28	.89
I24	If available, I plan to use LMS in the future.	4.24	.93
	Use Behavior		
I25	I use LMS to attain learning objectives in my classes.	3.98	1.07
I26	I use LMS to support the process of teaching and learning.	4.12	.95
I27	I use LMS for the transfer or creation of knowledge.	4.10	.99
*LMS self-efficacy****			
I28	I am confident about my ability to use LMS to complete my work.	4.18	.92
I29	I believe in my capability of using LMS to complete my work.	4.38	.79
I30	I have mastered the skills necessary for using LMS in my job.	4.01	.97

Note. SD = standard deviation of the mean. *Items were adapted from Venkatesh et al. (2003). **Items were adapted from Wrycza and Kuciapski (2018). *** Items were adapted from Zheng et al. (2018)

DATA ANALYSIS

Multiple linear regression and artificial neural network analysis (ANN) were used to examine the study questions and determine the correlations between the factors. At first, multiple linear regression analysis was used to investigate the impact of determinants on BI and behavior in the model. In order to test if the data had a normal distribution, the skewness and kurtosis values were evaluated, which is one of the prerequisites of multiple linear regression analysis. The skewness and kurtosis values of the variables are shown in Table 3.

Table 3. *Skewness and Kurtosis Values of the Variables*

Variable	*Skewness*	*Kurtosis*
Performance Expectancy	-.590	-.369
Effort Expectancy	-.508	-.473
Social Influence	-.496	-.428
Facilitating Conditions	-.384	-.411
Interactivity in LMS	.018	-.726
Area of Scientific Expertise	-.200	-.794
Behavioral Intention	-.748	-.160
Use Behavior	-.541	-.575
LMS self-efficacy	-.466	-.647

The skewness and kurtosis numbers in Table 3 can be used to determine if the series is normally distributed. Various opinions about skewness and kurtosis values indicate that these values can be acceptable in the assumption of normality within the range of -1 to +1 (Morgan et al., 2011).

For the current analyses with three and five predicted variables, Mahalanobis distance was employed based on criterion values of "16.27" and "20.52" (Tabachnick et al., 2001). As a result of the examination of Mahalanobis values, one outlier (extreme value) was found for the analysis with five predicted variables. However, no extreme values were found for the analysis with three predicted variables. For Pallant (2020), it is relatively unusual for a few outliers to arise; therefore, the study began with 105 people after one case was maintained in the dataset.

The existence of skewness and kurtosis values between -1 and +1 in the current study indicates that the scores have a normal distribution. The tolerance, variance inflation factor (VIF), and condition indices (CI) values for the predictor variables included in the study are also listed in Table 4.

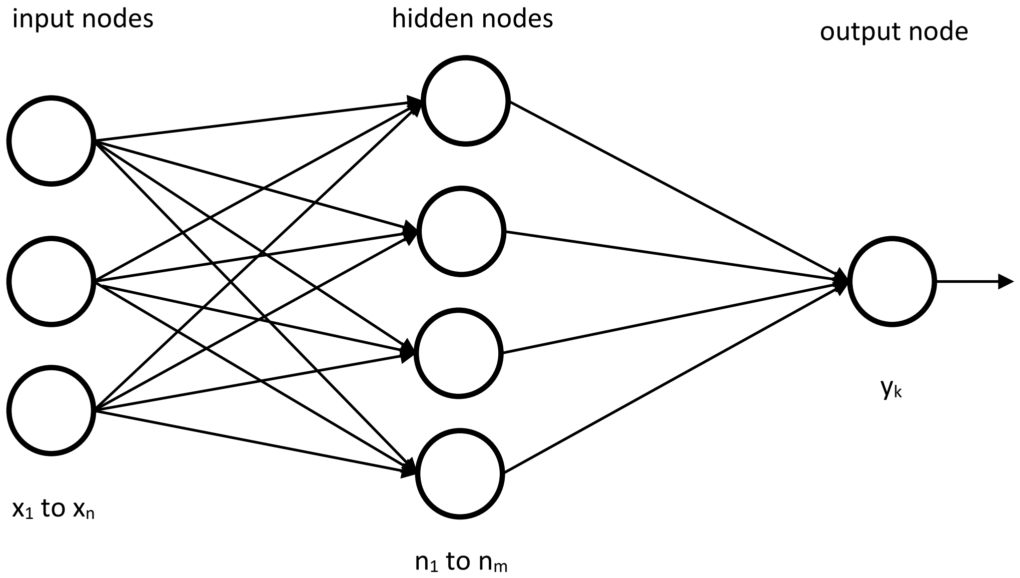
Table 4. *Tolerance, VIF and CI Values of the Predictive Variables*

Variable	*Tolerance*	*VIF*	*CI*
Performance Expectancy	.370	2.699	8.889
Effort Expectancy	.328	3.049	11.013
Social Influence	.431	2.319	12.150
Facilitating Conditions	.554	1.804	8.350
Interactivity in LMS	.700	1.428	10.125
Area of Scientific Expertise	.425	2.352	16.222
Behavioral Intention	.624	1.602	6.766
LMS self-efficacy	.290	3.442	13.367

The results in Table 4 show that the independent variables' tolerance value is more significant than 0.20, the VIF value is less than 10, and the CI value is less than 30. This finding indicates that these variables are not multicollinear (Petrini et al., 2012; Robinson & Schumacker, 2009). The IBM SPSS Statistics 22 package software was used to conduct the analysis. Lastly, Durbin-Watson values were examined to ensure that errors were independent. The closer to 2 that the value is, the better (Rutledge & Barros, 2002), and the Durbin-Watson statistics for BI and Use Behavior are 2.14 and 1.62, respectively, which are close to 2 that the assumption is most very definitely met.

The results of regression analysis were compared to those of ANN analysis, a mathematical model that reflects largely parallel, distributed processing systems and is inspired by the human brain's neural network topology (Greenwood, 1991; Haykin, 1999). To tackle complex problems in parallel, the ANN model uses many interconnected processing components (neurons) (Haykin, 1999). The ANN model is a supervised-based learning model, meaning it learns from pre-existing instances called training data. An ANN can be adjusted for a specific purpose, such as pattern recognition or data classification, using training or learning methods. An ANN is widely used to detect data patterns and solve complex interactions between inputs and outputs. An ANN model is commonly divided into three layers, as shown in Figure 2: input layers, hidden layers, and output layers. With x1, x2,...xn as inputs and yk as the output, ANN uses a hidden layer as a feed-forward mechanism. A weight is assigned to each input node, which is subsequently passed on to the hidden layer, which is made up of many hidden nodes.

Figure 2. *Sample ANN Model*



The ANN model is used in various information systems fields, including e-learning, because of its computing capacity and ability to handle various data (Scott & Walczak, 2009; Shmueli & Koppius, 2011; Simoncini et al., 2017). ANN models also have several advantages over typical statistical models. Because there are no preconceived assumptions about the input data distribution, they are characterized as non-parametric models. They can capture both linear and nonlinear interactions; traditional statistical models, such as the regression model, on the other hand, are categorized as parametric models since they are based on the assumption of specified data distribution (Hair et al., 2013).

BI and use behaviors of instructors were taken as the output variables in ANN analysis. In statistics, the output variable (sometimes known as the output layer) relates to the dependent variable. On the other hand, PE, EE, SI, Portal SE, and ASE are the predictive variables of BI. Moreover, the predictive variables of use behaviors are FCs, INT in Portal, and BI. The model's whole set of variables was subjected to an "adjusted normalized" transformation. The data set is split according to the relative case number assigned to random cases. Training data (TRD), testing data (TED), and validation data (VD) / holdout data (HD) are the three parts of this data.

When it comes to separating this data, there is no standard technique to consider. For Zhang et al. (1998), 80% (TRD), 20% (TED) or 70% (TRD), and 30% (TED) rates are often used to divide data into parts. In this study, 60% (TRD), 30% (TED), and 10% (HD) rates were used. The use of 10% verification data in this study was done to minimize fitting problems, an issue that needs to be resolved in machine learning applications like Artificial Neural Networks. The risk of overfitting is considerable if the ANN model works too much on the training data set and memorizes it or if the training set is uniform since the model begins to research for precise copies of conditions in the training set. Overfitting can be avoided when the data set is split in two using validation data or when the model is permitted to estimate using a less complex model. In small datasets, the cross-validation technique is extensively utilized. The application is made on the test set based on the training that took place on the training set. The cross-validation method divides the data set into halves and creates different training-test set pairs, allowing the model to run on a smaller data set. The dataset is split into three parts, 60% (TRD), 30% (TED), and 10% (HD), in this study so that the training data is not overworked, and the HD feature may be employed to avoid overfitting. Thus, training-test-holdout-sets were built, the model was trained on extra data, and overfitting preventative steps were implemented. During the analysis, IBM SPSS Statistic 22 pack was used, and the ANN model's architecture was constructed accordingly. The hyperbolic tangent function is utilized as the input activation function for hidden layers, whereas in automated architectural design, the identity function is used in the output units. The number of hidden layers is set to 1 in the automated architectural selection option. A three-layer network layout with one hidden layer is commonly utilized in the literature (Han & Wang, 2011; Hippert et al., 2001; Zhang et al., 1998). The "online" type of learning approach was chosen as the learning method in the ANN analysis since the data in the study are not totally independent of one another.

INSTRUMENT RELIABILITY

Cronbach's alpha was determined for the sub-scales within its scope to validate the questionnaire's internal consistency. The alpha values for each subscale are shown in Table 5. All reliability values were within acceptable limits ranging from .82 to .97.

Table 5. *Subscales' Alpha coefficients*

Subscale	*Items*	*Cronbach's Alpha*
Performance Expectancy	4	.925
Effort Expectancy	4	.880
Social Influence	3	.835
Facilitating Conditions	4	.824
Interactivity in LMS	3	.864
Area of Scientific Expertise	3	.921
Behavioral Intention	3	.969
Use Behavior	3	.940
LMS self-efficacy	3	.862
Total	30	

RESULTS

The preliminary research question was to see if the elements of PE, EE, SI, LMS SE, and ASE could predict BI. Multiple regression analysis was used to solve this research question. In Table 6, the model summary of the regression analysis for the BI of the academic staff towards the acceptance of LMS and the regression coefficients' findings are presented.

Table 6. *Regression Analysis Model Summary for Faculty Members' Behavioral Intention towards LMS Acceptance*

Predictors	*Adjusted R^2= .557* *F change= 27.113* *p= .000*		
	Coefficients		
	B	*Beta*	*Sig.*
(Constant)	34.312		.009
Performance Expectancy (PE)	.086	.149	.167
Effort Expectancy (EE)	-.020	-.034	.769
Social Influence (SI)	.017	.016	.873
LMS self-efficacy (SE)	.271	.256	.037
Area of Scientific Expertise (ASE)	.462	.450	.000

A regression analysis was carried out to answer the first research question, whether instructors' LMS SE, PE, EE, SI, and ASE factors can predict BI to use of LMS. Moreover, it found a significant result, R^2 =.578, F(5,99) = 27.113, p<.001, only in SE and ASE, which positively affected the scores regarding BI to use (see Table 6). The ASE, one of the two significant predictors of BI to use LMS, maybe a more significant predictor than SE (β_{ASE}=.450>β_{SE}=.256).

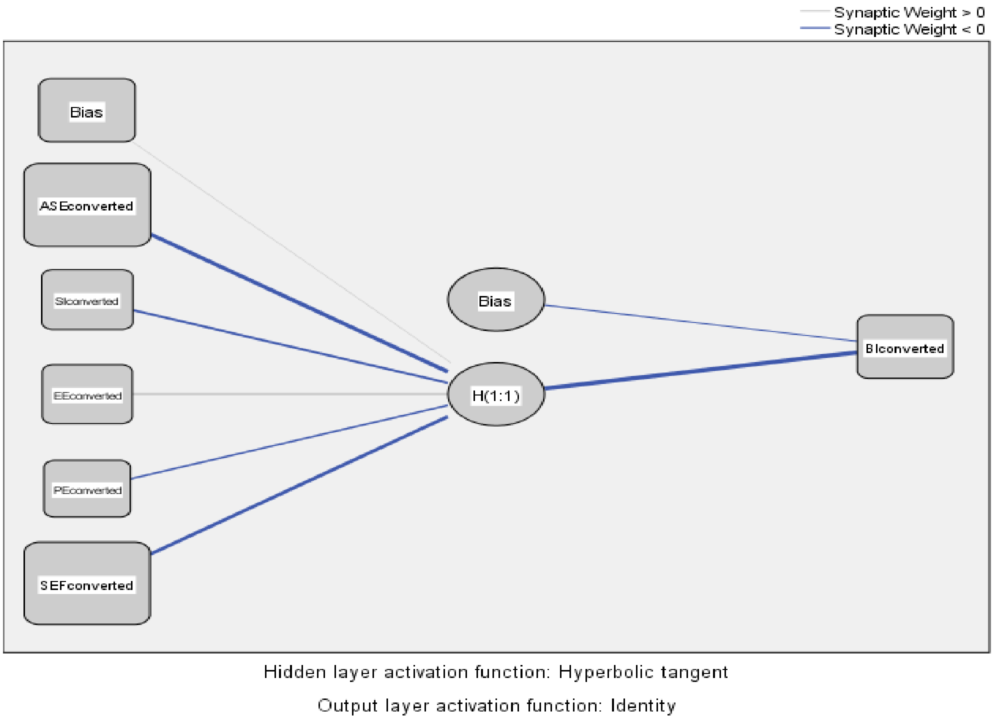
ANN analysis, in this study, was used to determine the instructors' BIs and the significance levels of the effective predictors in their use behavior, which were then compared to the regression analysis findings. According to the analysis, the Sum of Squares Error was found as 17.545, the Relative Error was found as .516 during the training, the Sum of Squares Error was 2.063, and the Relative Error was .225 during the testing phase. Relative Error increased to .245 while verifying. The IBM SPSS Statistic 22 tool bases its error calculations on the test sample. A brief overview of the data utilized in the ANN analysis is shown in Table 7.

Table 7. *ANN Data Run Summary*

	N	%
Training data	69	65,7%
Test data	28	26,7%
Holdout data	8	7,6%
Valid data	105	100,0%
Excluded data	0	
Total	105	

The whole data set was split into train (65.7%, n=69), test (26.7%, n=28) and validation (7.6%, n=8) as shown in Table 6. The whole data set was split into train (65.7%, n=69), test (26.7%, n=28) and validation (7.6%, n=8) as shown in Table 7. There is no excluded data, and all the data is valid. The structure of the developed ANN model and neural networks is shown in Figure 3.

Figure 3. *ANN Model Structure to the Behavioral Intention*



The ratings were defined in percentages to ascertain the importance of independent variables' ratings in line with the weights linking the artificial neural cells in the network, and Table 8 summarizes their findings.

Table 8. *Significance of the Independent Variables Related to the Behavioral Intentions of the Instructors*

Independent Variables	*Importance*	*Normalized Importance*
Area of Scientific Expertise (ASE)	.319	100.0%
Social Influence (SI)	.133	41.6%
Effort Expectancy (EE)	.126	39.5%
Performance Expectancy (PE)	.107	33.4%
Portal self-efficacy (SE)	.316	98.9%

When Table 8 is examined, it is clear that ASE (100%) is an essential independent variable for the artificial neural network constructed for the instructors' BIs. This independent variable is followed by the instructors' LMS SE (98.9%). This result is identical to the one obtained by regression analysis (Table 5). The most specific independent variables concerning beta values are ASE (=.450) and SE (=.256), which were statistically significant due to the regression analysis.

The second research question sought to ascertain the predictability of the factors, BI to use LMS, FCs, and INT features of instructors' use behavior of LMS. For this research question, multiple regression analysis was used. The model summary of the regression analysis for the instructors' use behavior towards LMS and the regression coefficients' results are shown in Table 9.

Table 9. *Regression Analysis Model Summary for the Usage Behavior of Instructors Towards LMS*

Predictors	*Adjusted R^2= .626 F change= 56.316 p= .000*		
	Coefficients		
	B	*Beta*	*Sig.*
(Constant)	-9.374		.485
Behavioral intention to use LMS (BI)	.414	.394	.000
Facilitating conditions (FC)	.226	.339	.000
Interactivity features of the LMS (IF)	.232	.215	.004

In a subsequent analysis, we examined whether the BI to use the LMS predicted use behavior, easing the conditions and interaction characteristics of the LMS. It produced a significant result, R^2=.626, $F(3,101)$=56.316, $p < .001$, indicating that all variables have favorable outcomes on the use behavior of the instructors (see Table 9). When the importance levels of the predictors of use behavior are analyzed, BI to use LMS (BI=.394) is the most important predictor, followed by Facilitating conditions (FC=.339) and LMS INT features (IF=.215).

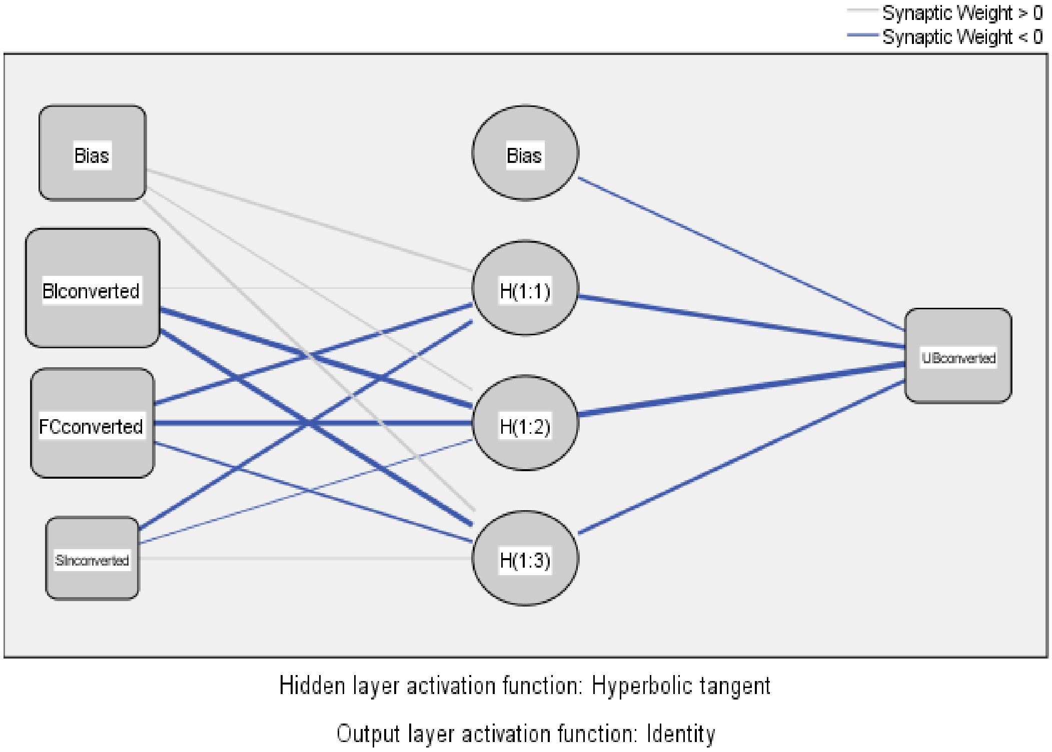
During training, the Sum of Squares Error was found to be 12.478, and the Relative Error was found to be .438 in an ANN analysis to evaluate the critical levels of predictors that are effective in the use behaviors of instructors. The Sum of Squares Error is 4.746, and the Relative Error is .277 during the testing phase. Relative Error became .543 after verification. The run summary of data used in the ANN analysis is shown in Table 10.

Table 10. *ANN Data Run Summary*

	N	*%*
Training data	58	55,2%
Test data	37	35,2%
Holdout data	10	9,5%
Valid data	105	100,0%
Excluded data	0	
Total	105	

Table 10 shows that the entire data set was divided into three categories: train (55.2 %, n=58), test (35.2 %, n=37), and validation (9.5%, n=10). There is no excluded data, and all of the data is valid. The structure of the developed ANN model and neural networks is shown in Figure 4.

Figure 4. *ANN Model Structure to the Use Behaviors of Instructors*



The ratings were defined in percentages to ascertain the importance of independent variables' rating in line with the weights linking the artificial neural cells in the network, and Table 11 summarizes their findings.

Table 11. *Significance of the Independent Variables Related to the Use Behaviors of the Instructors*

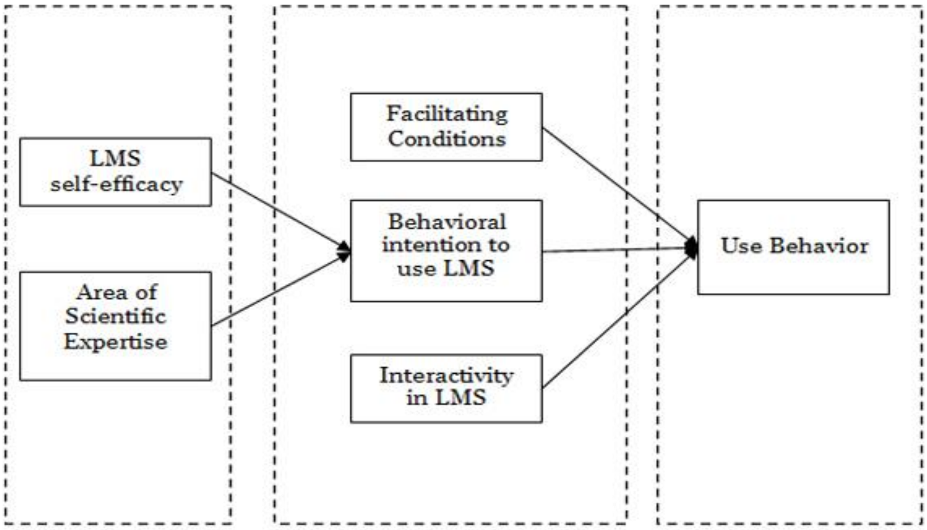
Independent Variables	*Importance*	*Normalized Importance*
BI	.487	100.0%
FC	.390	80.0%
IP	.123	25.2%

As can be noticed considering Table 11, the most important independent variable for the artificial neural network created for the BIs of the instructors is BI (100%). This argument is followed by FC (80%). This result is comparable to the one derived from the regression analysis (Table 8). According to the regression analysis, the most specific independent variables concerning beta values are BI (=.394) and FC (=.339), both of which are statistically significant predictors.

DISCUSSION, CONCLUSION AND IMPLICATIONS

Through the extended UTAUT model, the factors influencing instructors' BI to use and use behavior of LMS, which was optional to use, and their use behavior were scrutinized in this research. According to the analysis results, an explanatory model (see Figure 5) was developed that indicated instructors' BI to use LMS and LMS use behaviors. Using the UTAUT model, we found that, contrary to the literature, PE and EE are unreliable predictors of BI when using LMS.

Figure 5. *Factors Affecting Instructors' Use Behavior of LMS*



One of the factors affecting instructors' use intention is LMS SE. Instructors' BIs to use LMS are developing as they depend on their application skills. This result supports Bandura (1977)'s assertion that SE enhances active learning and that LMS SE may be viewed as an internal motivation factor that increases the BI to use LMS. In addition, this conclusion is now consistent with the findings of previous studies (Baki et al., 2018; Hsia et al., 2012; Ong & Lai, 2006). Instructors' BIs will diminish if they do not have adequate knowledge about LMS. Therefore, institutions may provide training to instructors on the use of LMS. The instructors' SE will improve if schools give training on using LMS to instructors in need at the start of each academic year. The investments will be utilized efficiently if the instructor believes s/he can accomplish it and is confident. According to this finding, the SE aspect should be added as a variable in research models in instructional technology studies, particularly those that use Venkatesh et al. (2003) UTAUT model.

Another aspect influencing BI to use is the instructors' ASE or their views on whether their courses are appropriate for LMS or online education. This study's findings contradict those of Wrycza and Kuciapski (2018), who found no direct influence of the ASE on BI. This result might be because the research groups are different. The study's findings may have been influenced by differences in LMS usage rules in the post-secondary military vocational institution where the research was conducted. Instructors intend to use LMS if they believe their courses can be supported by it. Again, if institutions provide examples from many areas of training to instructors and make instructors realize that there is something they can accomplish for their courses, their BI to use LMS will increase. According to the findings, one of the events is that the rate of instructors' use of LMS will grow in tandem with their desire to use it.

This research found no significant causal connection between PE and instructors' BIs to use LMS. This finding contradicts earlier research findings, which revealed that PE was highly beneficial in influencing BI (Venkatesh et al., 2003). The researchers' brief training to instructors on the use of LMS at the start of the academic year 2021-2022 and their motivation to utilize it could contribute to the insignificant relationship between PE and BI. Overall, it can be inferred that when institutions provide training to instructors on using LMS, their performance expectations rise.

Although the UTAUT (Venkatesh et al., 2003) model and Ain et al. (2016) revealed a significant link between EE and BI in using LMS, it was insignificant in this research. Furthermore, this conclusion is congruent with Wrycza and Kuciapski (2018) research. Additionally, practically all instructors are skilled in using the LMS due to the brief usage training offered at the start of the term having minimal impact on their intention to use the LMS. The finding of an insignificant association between EE and BI in using LMS is in line with Ain et al. (2016). They found an insignificant link between effort expectation and BI in the context of LMS. Again, the brief training provided to instructors at the beginning of the school year led the instructors' EEs unaffected by their BI to use the LMS.

Williams et al. (2015) systematic review and Taiwo and Downe's (2013) meta-analysis revealed that the connection between BI and SI is minor. They found that 29 out of 115 research that looked at this direct connection found it to be insignificant. Venkatesh et al. (2003) claim that the importance of SI on technical acceptability varies depending on the circumstances of the study. The connection between SI and BI was minor, as in our study (Khechine & Lakhal, 2018; Mtebe & Raisamo, 2014; Teo, 2011; Venkatesh & Zhang, 2010). This relation might be because the LMS is utilized voluntarily by willing instructors. This result contradicts prior studies' findings that SI predicts BI (Khechine et al., 2020).

BI, FCs, and INT in the LMS are all factors that influence instructors' use behavior. As previously shown in prior studies (Šumak & Šorgo, 2016), there is much evidence of an essential connection between BI to use and use behavior. This finding indicates that actual usage will be more significant if instructors intend to utilize LMS. As a result, institutions should adopt and support online learning to complement traditional lecture delivery.

Because there is a significant link between FCs and use behavior, technological and human support are crucial for instructors to use the LMS. This outcome aligns with earlier research (Dwivedi et al., 2019). It is critical for institutions to establish a support office that can assist instructors with the use of LMS, provide user guides, and offer appropriate LMS equipment. Institutions that facilitate instructors' activities will encourage more instructors to use LMS for their courses.

INT in LMS predicts instructors' LMS use behavior, indicating that if instructors can use LMS's INT qualities to cooperate and communicate with students, they will wish to use LMS. This result is comparable to Wrycza and Kuciapski (2018). This data means that instructors intend to use LMS to communicate with students and other instructors, believing that doing so will improve teaching performance and lesson management. Furthermore, for instructors to communicate with their students via LMS, the LMS should be adequately selected and suitable for messaging.

The scope of this study is one of its main limitations. Other users (such as students and administrators) were not considered for this study, which solely focused on post-secondary military vocational school instructors' LMS usage. Another notable limitation of this study is that the research was done with instructors working in a two-year military vocational school in Turkey. This study may shed light on future research and can be conducted in larger institutions with more instructors to extrapolate the results.

The instructors' perceptions were examined over a period. On the other hand, instructor perceptions of LMS change over time and experience, and the COVID-19 pandemic may have altered many views on LMS. In addition, this research collected data using a quantitative approach. Continuous research using a mixed data-gathering strategy, including instructors and students, could also be used in future research.

As stated in the literature review section, an extended UTAUT model was employed in this study; future research should test additional variables that could give more critical information about instructors' LMS use behavior.

Before the pandemic of the unknown coronavirus illness, much education took place in physical classrooms. The COVID-19 outbreak was a watershed worldwide, indicating that the educational system needed to be rethought. The outbreak triggered new approaches to teaching online (Almahasees et al., 2021). When viewed from this aspect, COVID-19 can be considered to have raised the educational bar. Virtual classes have taken over following school closures to avoid spreading the disease (Chandra, 2021).

Consequently, it proved that instructors should adopt LMSs or online education systems as a requirement rather than a choice. The finding of this research might be essential in enhancing online courses or LMS in post-pandemic normalcy; it is expected that online learning use will continue, particularly in a hybrid type. Irrespective of the type of course, having videos, lecture notes, and course materials that students can access remotely is critical for instructional continuity. Faculty and higher education institutions are responsible for implementing these systems. According to the conclusions of this research, beginning with the COVID-19 breakout, technology has undoubtedly become a vital tool in the educational sector. Therefore, higher education institutions should train instructors on how to utilize LMS efficiently, and instructors should use LMS.

What is expected of students and instructors varies in the modern era as technology advances. The effect of new factors (augmented reality, artificial intelligence, Etc.) on instructors' intention to use LMS can be examined in future studies. Furthermore, our research has proven that the ANN methodology may be used in similar studies, and the same method can be used in large-scale studies.

Because of UTAUT's limitations, this research has revealed a more accurate solution to measure aspects of LMS acceptance and use, including individual, technological, and environmental factors. This study adds to the body of knowledge about how instructors embrace and use LMS and our understanding of technology acceptance and use. The study's conclusions show that higher education institutions should educate instructors on how to use LMS and focus on providing helpful circumstances for instructors by establishing a support office. Also, an interactive LMS can be suggested for instructors to develop interactive learning environments in pedagogical practice. Moreover, instructors are encouraged to utilize the LMS to send messages to students and answer as quickly as possible, which can boost student-instructor interaction.

AUTHOR CONTRIBUTION

- First author have made substantial contributions to acquisition of data, analysis, and interpretation of data
-The second author have made substantial contributions to conception and design, and have been involved in drafting the manuscript
-The third author have reviewed the article and checked for typos

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