Factor Analysis of Learning Management System Acceptance

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Abstract

In this digital era, the development of information technology is increasingly sophisticated and integrated. In the education sector, the most integrated information technology tool is the Learning Management System (LMS). Several ministries in Indonesia have adopted LMS as a strategy to increase the competence of the state civil apparatus. Availability LMS has great organizational potential, but several studies have shown that LMS exhibits high failure rates. Therefore, this study aims to determine what factors encourage LMS acceptance so that LMS use can be maximized.
This quantitative research is conducted with factor analysis based on a combination of the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and Technology-to-Performance Chain (TPC) models. Data collection were carried out by conducting an online questionnaire survey to LMS users at the Human Resources Development Agency of the Ministry of Law and Human Rights. The data was processed using SPSS software with the Confirmatory Factor Analysis (CFA) method. This study resulted in two groups of new factors driving LMS acceptance rates: Management Support (factor 1) and Learning Facilities (factor 2).

Keywords
Learning Management System, Civil Apparatus, UTAUT2, TPC, Confirmatory Factor Analysis.

1. Introduction

Rapid advances in computing, storage, and internet technologies have made sharing and storing information much more effective and affordable (Shivdas et al. 2020). No exception in the education sector, information technology is used to improve the learning process (Zwain 2019) and provide opportunities for the education sector to improve its education system (Hernandez et al., 2011; Sharif et al. 2019). Technology integration brings many benefits, such as encouraging quality learning, improving technological skills, and encouraging learners to be interactive (Sharif et al. 2019).

In the education sector, the most integrated information technology tool is the Learning Management System (LMS) (Asiri et al. 2012; Sharif et al. 2019). LMS is one of the emerging information technology tools that facilitates e-learning and provides education without the limitation of time and place. It is a web-based system that allows instructors and students to interact and share information and resources (Ain et al. 2015). In Indonesia, besides being used in the education sector, LMS is also used in the government sector to improve civil apparatus competencies. Considering that Indonesia is an archipelagic country with a population of 270,20 million (Badan Pusat Statistik, 2020), LMS can facilitate them anywhere, anytime.

Based on Law Number 5 of 2014, every state civil apparatus has the right to obtain competency development of at least 20 hours of lessons/year. Several Ministries adopted LMS in Indonesia to facilitate this as a strategy for developing the competence of conventional civil apparatus toward modern concepts. One of them is the Ministry of Law and Human Rights of the Republic of Indonesia, which facilitates “Learning Home” as an LMS for the civil apparatus Ministry of Law and Human Rights throughout Indonesia. With this LMS, it is hoped that all state civil apparatus can develop themselves anytime and anywhere, both at the center and in the regions. LMS has also been connected to the staffing system so civil apparatus can compete according to their functional and structural positions. Therefore, the availability of LMS has excellent potential for organizations. However, some studies show that LMS exhibits higher failure rates than traditional learning methods (Rulevy & Aprilianti 2021). Thus, it is crucial to understand the factors that affect the user acceptance of LMS (Ain et al. 2015).

Human Resource Development Agency Ministry of Law and Human Rights, as one of the units of the Ministry of Law and Human Rights that functions to carry out human resource development, as well as a pioneer in "Learning Home," has the highest percentage of LMS users compared to other units, reaching 85%. It is hoped that the civil apparatus can genuinely accept this LMS in this unit before being accepted by the civil apparatus in other units. Therefore, this research will determine what factors influence LMS acceptance by the civil apparatus at the Human Resource Development Agency Ministry of Law and Human Rights.

Based on the explanation above, the writer wants to know more about what factors encourage the acceptance of LMS from the perception of its users. There are many theories regarding the acceptance of technology. Macedo (2017) stated that the Unified Theory of Acceptance and Use of Technology (UTAUT2) model has effectively explained behavioral intentions and the use of Information and Communication Technologies (ICT) among population groups (Macedo 2017). Sharif et al. (2019) explained that the UTAUT2 model with Task-Technology Fit (TTF) on the Technology-to-Performance Chain (TPC) model is not only well-integrated but also empirically important (Sharif et al., 2019). This model is also evidenced by several studies that integrate UTAUT2 and TTF, namely by Faqih & Jaradat (2019), Sharif & Afshan (2019), and Wan et al. (2020). Therefore, the authors confirm the variables in the UTAUT and TPC models. So that the research questions that will be answered in this study are:

1. What factors encourage LMS acceptance by civil apparatus at the Human Resource Development Agency Ministry of Law and Human Rights?
2. What factors contribute the highest value to the acceptance of LMS by civil apparatus at the Human Resource Development Agency Ministry of Law and Human Rights?

2. Literature Review

2.1 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The unified theory of acceptance and use of technology (UTAUT) is an acceptance model developed by Venkatesh et al. (2003) to determine what factors affect a person's interest in using a technology system. The UTAUT model consists of four main structures of behavioral intention and use behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al. 2003). Furthermore, Venkatesh, Tong, and Xu (2012) developed the UTAUT model, giving birth to three new structures: hedonic motivation, price values, and habits. While UTAUT is used in an organizational/enterprise context, UTAUT2 was developed to measure user behavior in a particular context. With the existence of the UTAUT2 model, it is expected to identify three essential structures in research on acceptance and better use of technology (Venkatesh et al. 2012). The UTAUT2 model that has been developed is as follows:

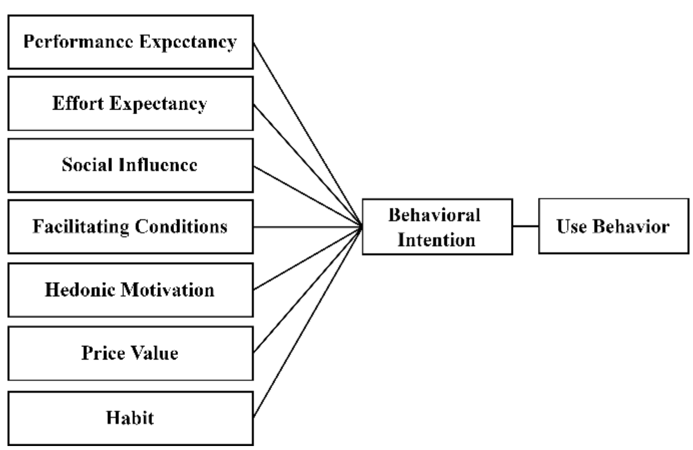

Figure 1. UTAUT2 Model

The UTAUT2 model covers both acceptance and use by consumers and has shown significant success in explaining interest and use. In Figure 1, UTAUT2 has refined seven variables: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit. Moreover, the intervening variable used is behavior intention, and the dependent variable is use intention. Age, gender, and experience become moderator variables. The following are the variables of UTAUT2.

a) Performance Expectancy: the level of trust that a person has with the use of technology that provides benefits and benefits to work (Vankatesh et al. 2003).
b) Effort Expectancy: the level of convenience users feel in using technology that can reduce a person's energy and time spent doing work (Venkatesh et al. 2012).
c) Social Influence: a belief that the closest person can influence and recommend the use of technology (Venkatesh et al. 2012).
d) Facilitating Condition: the level of confidence that users can implement the innovation in the presence of suggestions that support the use of the new technology.
e) Hedonic Motivation: a person's level of pleasure in using technology is essential in determining acceptance and use (Venkatesh et al. 2012).
f) Price Value: the level of comparison between the users' perceived benefits and the technology costs (Venkatesh et al. 2012).
g) Habit: the extent to which users use technology as a habit (Venkatesh et al. 2012).
h) Behavioral Intention: the extent to which a person will use specific technology in the future (Indrawati & Utama 2018).
i) Use Behavior: actual conditions of users of an application or information technology (Vankatesh et al. 2003).

2.2 Learning Value

The UTAUT2 model considers the costs incurred for the use of technology, namely the 'Price Value' construct, which is used as a 'consumer' cognitive tradeoff between the perceived benefits of the technology and the monetary costs of using it (Venkatesh et al., 2012; Dodds et al. 1991). Perception of price value positively affects the intention to use technology (Ain et al., 2015). In addition, Ain et al. (2015) note that all UTAUT2 studies in learning technology ignore the value-price construct because educational technology usually does not include additional user costs. Thus, Learning Value (LV) was introduced instead of Price Value (PV) to close the gap. Learning Value (LV) is defined as the perceived value of learning technology for the time and effort spent (Zwain 2019; Ain et al. 2015). Based on this, in this study, the 'Price Value' variable in the UTAUT 2 model will be replaced with Learning Value.

2.3 Technology-to-Performance Chain (TPC)

Technology-to-Performance Chain (TPC) presents a comprehensive model of two complementary things, namely Task-Technology Fit (TTF) and technology utilization (Utilization). TPC is a user behavior-based information technology system model developed by Goodhue & Thompson (1995) to improve organizational performance. The TPC model is built by combining two theories, namely fit theory and utilization theory, to explain the relationship between the variables of user tasks, information technology used, suitability of technology tasks, use of information systems, and user performance (Goodhue & Thompson 1995). In varying degrees of benefit, a system with a higher task-technology suitability will result in better performance, as it better meets the needs of the individual task. The TPC model is presented in Figure 2.

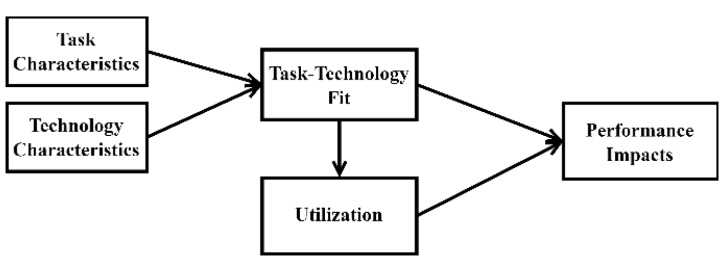

Figure 2. TPC Model

Figure 2 shows that the TPC consists of 5 (five) variables, including the following.

a) *Task Characteristics*

Task Characteristic is that users may use information technology to perform their tasks. In the perspective of TTF, a task is defined as actions taken by individuals in converting inputs into outputs to meet their information needs (Goodhue & Thompson 1995). Tasks can vary on several dimensions: non-routine tasks, task interdependence, and time criticality (D'Ambra et al. 2013).

b) *Technology Characteristics*
Technology is a tool (hardware, software, and data) used to help complete a task (Goodhue & Thompson 1995). The attributes of this technology can affect the use and users' perception of the technology. Research shows that better fit increases perceived performance (D'Ambra et al. 2013).

c) *Task-Technology Fit* (TTF)
Task-Technology Fit (TTF) describes how technology can help someone do their job (Tam & Oliveira 2017). Goodhue and Thompson (1995) state that TTF is an interaction between task, technology, and individual characteristics. TTF is based on the idea that system usage and user performance will improve when task and information technology characteristics are well-integrated. Therefore, TTF illustrates that users will only accept technology if it is valid and can help them improve task performance (Goodhue & Thompson 1995).

d) *Utilization*
Goodhue and Thompson (1995) stated that utilization is an individual's decision to use or not to use the applied technology. Information technology benefits users' expectations of information systems in carrying out their duties. The measurement of the utilization of information technology is based on the intensity and frequency of utilization. At a utilization rate greater than zero, a technology with a higher TTF will provide better performance (Goodhue & Thompson 1995).

e) *Performance Impacts*
Performance is the achievement of a portfolio of tasks by an individual. High performance implies a high degree of task-technology fit and satisfaction with IT (Goodhue & Thompson 1995). TTF and its high utilization will increase Performance Impacts.

2.4 Research Framework

In this study, 7 (seven) elements of UTAUT2 were used, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Hedonic Motivation (HM), Price Value (PV), Habit (HT). In this study, the moderating variables of age, gender, and experience will not be used as in the UTAUT2 model from Venkatesh et al. (2012), considering the purpose of this study is to analyze the acceptance factor of the Learning Home, which is descriptive and not causal. However, considering this research examines the acceptance of learning technology that is not paid for, the Price Value (PV) variable will be replaced by Learning Value (LV).

In addition to UTAUT2, the TPC model was chosen because it was essential to determine user perceptions regarding the alignment between technology characteristics and users' tasks (Faqih & Jaradat, 2021). The task characteristics and technology characteristics variables were not used because, in the factor analysis, the variables used could not be graded. The variables that can be used are TTF and Utilization. Meanwhile, according to Sharif et al. (2019), the UTAUT2 model with TTF is not only well-integrated but also empirically important (Sharif et al. 2019). This model is also evidenced by several studies that integrate UTAUT2 and TTF, namely by Faqih & Jaradat (2019), Sharif & Afshan (2019), and Wan et al. (2020). Therefore, the authors conducted a factor analysis based on the variables in the UTAUT2 and TPC integration models. The following framework of thought in this research is shown in Figure 3.

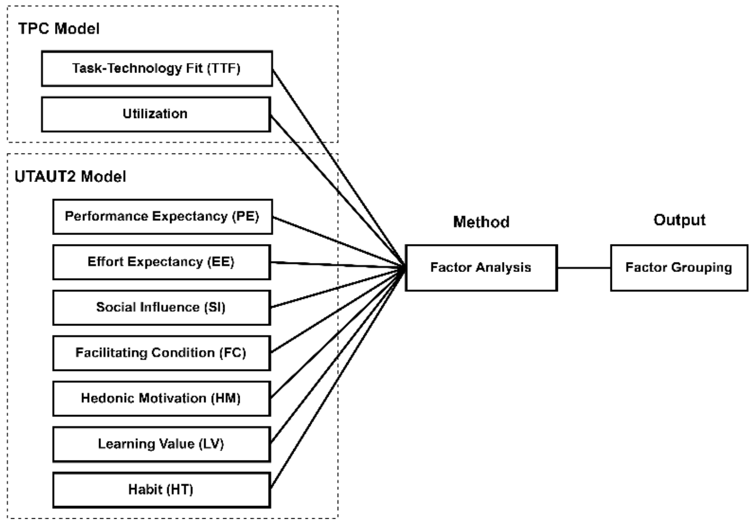

Figure 3. *Research Framework*

Based on the variables in the UTAUT 2 and TPC models, then factor analysis was carried out using Confirmatory Factor Analysis so that the factors that encourage the acceptance of LMS by the civil apparatus at the Ministry of Law and Human Rights are obtained.

3. Methods

This research uses a quantitative method with a descriptive research type. It begins with the stage of collecting data from primary and secondary data. Secondary data is obtained from literature studies, such as journals, articles, books, etc. While the primary data was obtained from the questionnaires distributed to the target population, namely state civil apparatus who have used Learning Home. The questionnaire was distributed online (google forms) using a 5-point Likert scale.

The sampling technique used is purposive sampling involving a population of 350 state civil servants who have used LMS. Questionnaires are distributed to each unit in the Human Resource Development Agency Ministry of Law and Human Rights and collected after three months. The sample size is determined from the Slovin formula, which can determine the sample size from a general population (Sugiyono 2017:81) so that a total sample of 187 is obtained. Furthermore, it was analyzed using the Confirmatory Factor Analysis (CFA) method using SPSS version 25 software.

4. Results and Discussions

4.1 Descriptive Analysis

Descriptive analysis is used to view the description of the data from the respondent's responses. Through the description of the response data, it can be seen how the condition of each variable being studied is. Table 1 shows the percentage of LMS acceptance for each variable.

In Table 1, based on the results of distributing questionnaires to 187 LMS users, the percentage of respondents' responses regarding LMS acceptance is 86.84%. With special categories on the continuum line. The highest percentage was achieved by Social Influence (SI) factor, which reached 89.39%, followed by the Performance Expectancy (PE) factor reaching 88.20%, and the Utilization (UT) factor reaching 87.99%. At the same time, the lowest percentage is the LV factor, which is 82.94%.

Table 1. The Results of Descriptive Analysis

Variable	Score	% Score	Categori
TTF	2438	86.92%	Very good
UT	2468	87.99%	Very good
PE	2474	88.20%	Very good
EE	2447	87.24%	Very good
SI	3343	89.39%	Very good
FC	3212	85.88%	Very good
HM	2443	87.09%	Very good
LV	3102	82.94%	Good
HT	2410	85.92%	Very good
Average	**2704.111**	**86.84%**	**Very good**

Factor Analysis

Kaiser Mayer Olkin (KMO) and Bartlett's Test of Sphericity

The first step in factor analysis is the Kaise-Meyer Olkin (KMO) Measure of Sampling Adequacy (MSA) test and the Barlett Test of Sphericity to determine whether or not factor analysis is feasible. If the index value is high (ranging from 0.5 to 1.0), factor analysis is feasible, but if the KMO value is below 0.5, factor analysis is not feasible. Meanwhile, Barlett's test of sphericity is used to test the correlation between variables. If Barlett's test of sphericity is significant, it shows that the correlation matrix has a significant correlation with several variables. The following table shows the results of KMO and Barlett testing with the help of SPSS 25 software.

In the output table above, it can be seen that the KMO – MSA value of 0.962 (greater than 0.5) indicates that the variable can be predicted and can be analyzed further. The significance value of Bartlett's Test of Sphericity is 0.000 (less than 0.05), indicating that the research variables can be predicted and analyzed further.

Table 2. Kaiser-Meyer Olkin (KMO) and Barlett Test Result

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.962
Bartlett's Test of Sphericity	Approx. Chi-Square	8458.506
	df	435
	Sig.	0.000

Anti-Image Matrices

In addition to the KMO – MSA value, which is similar to factor analysis, this is also supported by the results shown by Anti-Image Matrices. The value must be greater than 0.5 because this number shows how much other indicators can explain an indicator, so the bigger, the better. Table 3 shows the Anti-image Matrices value of each indicator. This table shows that all indicators already have an Anti-Image Correlation Value above 0.5, so that the analysis can be continued.

Table 3. Anti-Image Matrices Value

Item	*Anti-image Matrices*	Item	*Anti-image Matrices*	Item	*Anti-image Matrices*
TTF1	0.961	EE2	0.956	HM1	0.953
TTF2	0.976	EE3	0.946	HM2	0.967
TTF3	0.970	SI1	0.967	HM3	0.966
UT1	0.977	SI2	0.955	LV1	0.974
UT2	0.947	SI3	0.976	LV2	0.953
UT3	0.959	SI4	0.945	LV3	0.950
PE1	0.962	FC1	0.948	LV4	0.977

PE2	0.964
PE3	0.985
EE1	0.940

FC2	0.946
FC3	0.965
FC4	0.957

HT1	0.975
HT2	0.967
HT3	0.966

Determining the Number of Factors
Determining the number of factors needed to represent the variables to be analyzed is based on the magnitude of the eigenvalue and the percentage of the total variance. Only factors with one eigenvalue are retained in the factor analysis model, while the others are excluded from the model. The table of results for Total Variance Explained is shown in Table 4.

Table 4 shows that only two factors have an eigenvalue of more than 1, namely factor 1 and factor 2, with eigenvalues of 22.753 and 1.183, respectively. For clarity, factors 1 and 2 are marked with gray shading. While factors 3 to 30 are not used because the eigenvalues do not meet the requirements, which are less than 1. In addition, Table 4 shows that the percentage variance of each factor is 75.845% for factor 1 and 3.945% for factor 2. Thus, the two factors formed can explain the total percentage of 79.789% of all existing variables.

Table 4. Total Variance Explained

Factor	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	22.753	75.845	75.845
2	1.183	3.945	79.789
3	0.776	2.588	82.378
4	0.578	1.927	84.305
5	0.469	1.563	85.868
6	0.430	1.432	87.300
7	0.388	1.295	88.595
8	0.352	1.175	89.770
9	0.333	1.109	90.878
10	0.296	0.986	91.864
11	0.260	0.866	92.730
12	0.242	0.805	93.535
13	0.198	0.659	94.194
14	0.188	0.625	94.819
15	0.164	0.546	95.365
Extraction Method: Principal Axis Factoring.			

Factor	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
16	0.154	0.514	95.879
17	0.142	0.473	96.351
18	0.135	0.452	96.803
19	0.128	0.427	97.230
20	0.121	0.404	97.634
21	0.111	0.370	98.004
22	0.097	0.324	98.327
23	0.087	0.291	98.618
24	0.080	0.265	98.884
25	0.071	0.238	99.122
26	0.069	0.230	99.351
27	0.062	0.206	99.558
28	0.057	0.189	99.746
29	0.040	0.135	99.881
30	0.036	0.119	100.000
Extraction Method: Principal Axis Factoring.			

Factor Rotation
Sutopo and Slamet (2015) stated that factor rotation must be carried out. Hence, there are no difficulties interpreting new factors and in this study, using orthogonal rotation with the varimax procedure (variance of maximum) because it produces a simple factor structure by maximizing the amount of variance of the factor containing the loading squared value. The results of factor rotation are shown in Table 5.

Table 5 shows the distribution of the extracted variables into the formed factor based on the factor loading after the rotation process is carried out. Each indicator shows its rotation value for factor 1 and factor 2. If the value of factor 1 is more significant than factor 2, then the indicator is grouped into factor 1 and vice versa. The grouping of each indicator is marked with gray shading.

Table 5. Factor Rotation Value

Rotated Factor Matrix[a]		
	Factor	
	1	2
TTF1	0.710	0.509
TTF2	0.697	0.545
TTF3	0.722	0.523
UT1	0.695	0.527
UT2	0.673	0.559
UT3	0.683	0.588
PE1	0.781	0.413
PE2	0.788	0.432
PE3	0.700	0.591
EE1	0.672	0.525
EE2	0.574	0.609
EE3	0.766	0.374
SI1	0.838	0.341
SI2	0.745	0.398
SI3	0.757	0.378
SI4	0.801	0.447
Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization.		
a. Rotation converged in 3 iterations.		

Rotated Factor Matrix[a]		
	Factor	
	1	2
FC1	0.721	0.495
FC2	0.631	0.621
FC3	0.597	0.637
FC4	0.436	0.718
HM1	0.706	0.528
HM2	0.674	0.601
HM3	0.571	0.618
LV1	0.599	0.669
LV2	0.347	0.863
LV3	0.296	0.839
LV4	0.508	0.743
HT1	0.543	0.761
HT2	0.601	0.699
HT3	0.582	0.717
Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization.		
a. Rotation converged in 3 iterations.		

Factor Naming

The next step is to simplify the naming of the formed factors; the statement items of each factor are sorted according to their factor loading, as shown in Table 6. Based on Table 6, the researcher tried to do factor naming by identifying each statement item and the relationship between each item in one factor.

Factor 1, *Management Support*

Factor 1 consists of 19 statement items originating from Social Influence variables, namely items SI1, SI2, SI3, Performance Expectation variables, namely items PE1, PE2, PE3, Task Technology Suitability variables, namely TTF1, TTF2, TTF3, Utilization variables namely UT1, UT2, UT3, total 2 of 3 statements of Business Expectation variables, namely EE1 and EE3, some three statements of Hedonic Motivation, namely EE1 and EE3, and 2 of 4 statements of Supporting Conditions, namely FC1 and FC2. The author calls it "Management Support" because the name represents all statements, especially the statement item with the highest loading factor, namely Social Influence (SI1, SI2, and SI3), which refers to how agencies and the surrounding environment influence users to use LMS.

Factor 2, ***Learning Facility***

Factor 2 consists of 11 statement items originating from Learning Value variables, namely items LV1, LV2, LV3, LV4, Habit variables, namely items HT1, HT2, HT3, a total of 2 of 4 statements of Facilitating Condition variables, namely FC3 and FC4, a total of 1 of 3 Hedonic Motivation variable statement, namely EE2, and 1 of 3 Effort Expectancy variable statements, namely EE2. The author calls this factor "Learning Facility" because it can represent all statements, especially the statement with the most significant loading factor, namely Learning Value, which all refers to the perceived value of the LMS facility compared to the time and effort spent using it. Besides that, even for the statement on the Habit item, "Learning Facility" is sufficient to describe how existing facilities influence habits. Meanwhile, the statement item Facilitating Condition (FC3 and FC4) describes the suitability of existing facilities to motivate the use of LMS.

Table 6. Grouping of Statement Items according to the Order of Factor Loading

Factor	Item	Statement	*Factor Loading*
1	SI1	My leaders thought that I should use the Learning Home.	0.838
	SI4	Human Resource Development Agency Ministry of Law and Human Rights has supported the use of Learning Home in increasing competence	0.801
	PE2	Learning Home allows me to improve competence faster	0.788
	PE1	Learning Home is useful for increasing competence	0.781
	EE3	My interactions with the Learning Home in learning activities are clear and understandable	0.766
	SI3	My leader will support the use of Learning Home in increasing competence	0.757
	SI2	People in my neighborhood think that I should use Learning Home	0.745
	TTF3	In general, the function of the Learning Home fully meets my needs	0.722
	FC1	I have sufficient resources to use the Learning Home in improving my competence	0.721
	TTF1	I think the function/feature of the Learning Home is enough to help me improve my competence	0.710
	HM1	I feel happy using Learning Home	0.706
	PE3	Learning Home increases productivity in improving competence	0.700
	TTF2	I think the function/feature of the Learning Home is appropriate to help me improve my competence	0.697
	UT1	I am currently using Learning Home for competency development purposes	0.695
	UT3	I use Learning Home for comprehensive learning	0.683
	HM2	I enjoy using Learning Home	0.674
	UT2	I use Learning Home as a learning application	0.673
	EE1	Learning Home is easy to use	0.672
	FC2	I have sufficient knowledge to use the Learning Home to increase competence	0.631
2	LV2	In less time, Learning Home allows me to get or share learning references quickly and easily	0.863
	LV3	Learning Home gives me the opportunity to decide on the steps to improve my competence	0.839
	HT1	Using the Learning Home has become a habit for me	0.761
	LV4	Learning Home gives me the opportunity to increase my knowledge and to control my success (through competency targets and achievements)	0.743
	FC4	I think I can get help from other people when I have difficulty using Learning Home to improve competence	0.718
	HT3	I have to use Learning Home to improve competence	0.717
	HT2	I am addicted to using Learning Home to improve competence	0.699
	LV1	Learning through Learning Home is worth more in terms of time and effort given to increase competence	0.669
	FC3	The use of Learning Home in my learning activities is compatible with other technologies that I use	0.637
	HM3	Using Learning Home is very entertaining	0.618
	EE2	Learning Home easy to learn	0.609

Discussion

Based on research results, 2 (two) new factors have been formed that influence the acceptance of LMS by the civil apparatus at the Human Resource Development Agency Ministry of Law and Human Rights. Based on the value of Variance Explained as shown in Table 4, it is known that the two factors that significantly determine employee satisfaction in performance appraisals are Social, Technology, and Performance factors (factor 1) which can be considered the most dominant determinants of employee satisfaction in performance appraisals, with a value of 75.845%. Furthermore, the Learning Facility factor (factor 2) can explain 3.945% of the total Variance.

Based on the previous framework, 9 (nine) determinants of learning technology acceptance exist. Meanwhile, based on the results of research data processing, these nine factors were reduced to 2 (two) factors that significantly affected the acceptance of Learning Home by the civil apparatus at the Human Resource Development Agency Ministry of Law and Human Rights. These factors can be seen in Figure 4.
With the formation of 2 (two) factors that significantly determine the acceptance of civil apparatus to the Learning Home, it has answered the research questions.

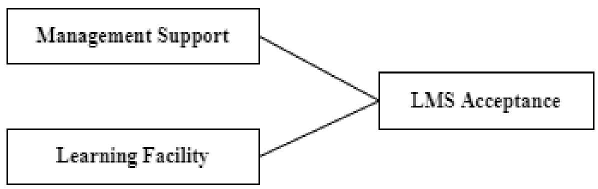

Figure 4. Determinants of Acceptance of LMS by Civil Apparatus

Conclusion and Further Research

Based on the results of data collection, data processing, and analysis that has been carried out, the authors can draw conclusions that answer the formulation of the problem from this research, namely as follows:

1. From the nine factors that influence the acceptance of learning technology, two significant factors are formed to determine the acceptance of “Learning Home” by the civil apparatus at the Human Resource Development Agency Ministry of Law and Human Rights. Based on the value of Variance Explained with data processing using SPSS version 25, it is known that these two factors are Management Support and Learning Facility, each of which can explain 75.845% and 3.945% of the total Variance.
2. From the two newly formed factors, there are several dominant variables each factor, including: "My leaders think that I should use the Learning Home." contained in the Management Support factor, and "In a shorter time, Learning Home allows me to get or share learning references quickly and easily" on the Learning Facility factor. Nevertheless, the most dominant factor in motivating in use of “Learning Home” is the Management Support factor which has the highest variance value among the other three factors, which is 75.845%.

This research was conducted in only one case in a government institution. Further research is expected to be carried out for a larger population. In addition, further research can also develop measurement instruments for each variable that has been found and tested empirically. Thus, the results can be used as a comparison to find out more deeply what factors affect the acceptance of LMS by its users.

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