Analysis of Factors Influencing the Utilization of LinkedIn Learning with Technology Acceptance Model Approach (Case Study of PT Semiconductor Batam)

Rahmat Hidayat[1] , Assyfa Naysila[2]

{rahmat@polibatam.ac.id[1], assyfanaysila00@gmail.com[2]}

Politeknik Negeri Batam, Business and Management Department, Batam City, Indonesia[1,2]

Abstract. This study aims to analyze the factors that influence the use of LinkedIn Learning with the Technology Acceptance Model (TAM) approach. The object of this research is the employees of PT Semiconductor Batam. The type of approach in this research is a descriptive quantitative approach with a research sample of 96 people. Data analysis was carried out using the PLS-SEM method with the SmartPLS 4.0 application. The results of this study prove that perceived ease of use has a positive and significant effect on perceived usefulness, perceived usefulness has a positive and significant effect on attitude towards using, perceived ease of use has a positive and significant effect on attitude towards using, attitude towards using has a positive and significant effect on behavioral intention, and behavioral Intention has a positive and significant effect on actual usage.

Keywords: Technology Acceptance Model, E-Learning, LinkedIn Learning, PLS-SEM

1 Introduction

Learning is a solution and strategy for individuals and companies with the aim of adapting and acting effectively to improve competence and create competitive advantage [1]. In line with this, the growth of information technology (IT) has also created a new culture for all individuals around the world including in terms of knowledge. One of the results of the integration of information technology into the world of knowledge and learning is E-Learning. E-learning is a distance learning concept that develops teaching and learning process through technology and digital media [2]. The main purpose of E-Learning in a company is digital utilization in improving the expertise of the employees as part of the HR management process. E-Learning implementation has been implemented by many companies, one of which is PT Semiconductor Batam. PT Semiconductor Batam is a company engaged in the production and management of IC (Integrated Circuit) components. In accordance with the vision of PT Semiconductor Batam, *we are the link between the real and digital world*, with the aim of motivating to keep moving forward in achieving digital transformation. In line with this vision, PT Semiconductor Batam also implements it to supporting self-development and competence-development for all of the employees by providing E-Learning in the company.

ICAESS 2023, November 07, Batam, Indonesia

DOI 10.4108/eai.7-11-2023.2342405

Since 2019, PT Semiconductor Batam facilitates self-learning based E-Learning (LinkedIn Learning) access to all its employees including internal employees, apprentices, and intern students by using personal windows account of PT Semiconductor Batam.

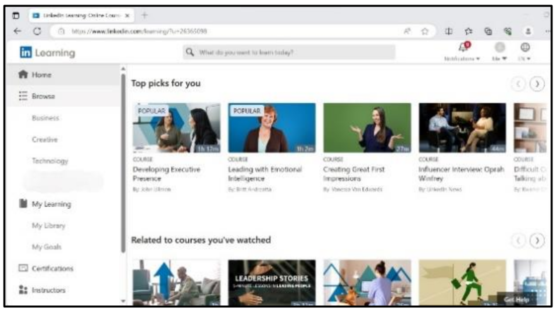

Figure 1 LinkedIn Learning view

LinkedIn Learning is a self-learning and e-learning platform equipped with 16,000 high-quality training videos, with 3 learning categories such as business, technology, and creative to deepen knowledge and develop individual skills.

Table 1. Number of active users of LinkedIn Learning

Fiscal Year 2021-2022 (FY2122)		
Month	**Active Users**	**People Logged In**
October'21	904	302
November'21	905	285
December'21	910	202
January'22	922	185
February'22	925	225
March'22	947	249
April'22	974	263
May'22	974	208
June'22	993	233
July'22	1051	288
August'22	1304	343
September'22	1804	911

Based on the table above regarding the number of active users and the number who accessed LinkedIn Learning in FY2122, it shows fluctuating numbers and most of them have not reached 50% of users compared to account owners every month. This shows that LinkedIn Learning facilities are still not optimally utilized by employees. Based on this, an important aspect that needs to be considered is the users who use LinkedIn Learning. This is because the level of user acceptance and readiness for E-Learning implementation can affect the optimal utilization of facilities provided by the company.

One of the models that can be used in explaining internal factors towards the acceptance of a technology is the Technology Acceptance Model that previously presented by Davis [3]. It was introduced as a theoretical extension of the Theory of Reasoned Action, which has found that TAM is able to explain user acceptance better, with perceived usefulness and perceived ease of use as the main drivers in technology acceptance. There are several previous studies with similar topics, namely a study revealing the results of the analysis of acceptance of the use of E-Learning using TAM, with the conclusion that the variables perceived usefulness and perceived ease of use have a positive effect on the acceptance of IT [4]. In addition, other research on E-Learning evaluation with TAM approach shows a positive influence on all variables, namely perceived usefulness, perceived ease of use, attitude toward using, behavior intention to use, and actual usage [5].

As outlined in the background information provided, it becomes evident that the analysis of technology acceptance, according to TAM theory, is essential for identifying factors influencing technology adoption. Consequently, researchers initiated a study aimed at discerning the determinants affecting the utilization of LinkedIn Learning. This investigation involved variables such as perceived ease of use, perceived usefulness, attitude towards usage, behavioral intention, and actual usage.

2 Literature Review

2.1 E-Learning

E-learning is a modern form of conventional learning methods, where the learning content is adapted in digital form and accessed through information technology [6]. The application of e-learning today shows a variety of approaches, but all of them rely on the principle or idea that e-learning refers to the effort of disseminating learning materials through the internet or electronic media [7]. In the realm of business and industry, e-learning is considered to have the potential to support the process of improving employee competence or human resources. In e-learning, there are three key elements. First, e-learning is connected through an electronic network that facilitates the delivery of information. Second, e-learning is delivered to users using computers by utilizing the internet network. Third, this learning approach goes beyond traditional training methods by including the provision of information and tools to improve performance [8].

2.2 LinkedIn Learning

LinkedIn Learning is a self-learning e-learning platform with 16,000 high-quality training videos, content focusing on technical and non-technical topics available in 7 languages, and 3 learning categories consisting of business, technology, and creative.

Business
The business category consists of professional development, leadership & management, customer service training, performance management training, HR training, digital transformation, online marketing training, social media marketing, etc.
Technology
The technology category consists of internet of things, data science, database management, IT infrastructure training, mobile development, software development, cloud computing, etc.
Creative
The creative category consists of art and illustration, photography, user experience, motion graphics, design thinking, creative thinking, creative collaboration, 3D and animation, etc.

2.3 Technology Acceptance Model

Davis [3] explained in TAM, there is a detailed explanation of the dimensions used to measure how technology is accepted by users, and how this affects the level of adoption of the technology. In the TAM model, acceptance of use is shaped by two primary factors: perceived ease of use and perceived usefulness.

3 Research Methods

This research is a research with a quantitative approach. The population of this study are employees of PT Semiconductor Batam with total 2,320 employees, using the Slovin formula which resulted in a sample size of 96 people. The data obtained then analyzed using PLS-SEM with measurement model and structural model through SmartPLS 4.0 application.

4 Results and Discussion

4.1 Descriptive Statistical Analysis

Respondent's Department

Table 2. Respondent's Department

Department	Total	Percentage
Communications (Comm)	3	3%
Development (Dev)	6	6%
Facilities Management (FM)	12	13%
Finance (Fin)	2	2%
Fronted Quality Management (FQM)	1	1%
Human Resources (HR)	16	17%
Industrial Engineering (IE)	10	10%
Information Technology (IT)	6	6%
Logistics (Log)	5	5%
Operation Planning & Control (OPC)	1	1%
Quality Management (QM)	11	12%
Segment Operation (SO)	22	23%
Test Technology & Innovation (TTI)	1	1%
Total	**96**	**100%**

Table above shows respondents based on department, from Comm (3%), Dev (6%), FM (13%), Fin (2%), FQM (1%), HR (17%), IE (10%), IT (6%), Log (5%), OPC (1%), QM (12%), SO (23%), and TTI (1%).

Respondent's Gender

Table 3. Respondent's Gender

Gender	Total	Percentage

Male	48	50%
Female	48	50%
Total	**96**	**100%**

Table above shows the respondents based on gender, male (50%) and female (50%).

Respondent's Age

Table 4. Respondent's Age

Age	**Total**	**Percentage**
17 - 25 Years	49	51%
26 - 35 Years	22	23%
36 - 45 Years	13	14%
>45 Years	12	12%
Total	**96**	**100%**

Table above shows respondents based on age. Age of 17-25 years old (51%), age 26-35 years old (23%), age 36-45 years old (14%), and age >45 years old (12%).

Respondent's Education

Table 5. Respondent's Education

Education	**Total**	**Percentage**
High School	12	13%
Diploma/Bachelor's Degree	76	79%
Postgraduate	8	8%
Total	**96**	**100%**

Table above shows respondents based on education level. High school level (13%), Diploma / Bachelor level (79%), and Postgraduate level (8%).

Respondent's Working Period

Table 6. Respondent's Working Period

Working Period	**Total**	**Percentage**
0 - 3 Years	60	62%
4 - 7 Years	12	13%
8 - 10 Years	5	5%
>10 Years	19	20%
Total	**96**	**100%**

Table above shows respondents based on working period, 0-3 years of working period (62%), 4-7 years of working period (13%), 8-10 years of working period (5%), and >10 years of working period (20%).

4.2 Outer Model Evaluation

The outer model evaluation aims to assess validity through convergent validity and discriminant validity, and reliability through composite reliability.

Convergent Validity Test

To assess convergent validity using reflexive indicators, you can examine the loading factor value of each indicator within the construct. The recommended loading factor value is above 0.70, but a loading factor of 0.5 - 0.6 can be said as sufficient [9].

Table 7. Outer Loading

Variable	Indicator	Outer Loading	Status
Attitude Towards Using	ATU1	0,879	Valid
	ATU2	0,908	Valid
	ATU3	0,780	Valid
	ATU4	0,861	Valid
Actual Usage	AU1	0,757	Valid
	AU2	0,887	Valid
	AU3	0,814	Valid
Behavioral Intention	BI1	0,859	Valid
	BI2	0,858	Valid
	BI3	0,825	Valid
	BI4	0,851	Valid
	BI5	0,720	Valid
Perceived Ease of Use	PEU1	0,666	Valid
	PEU2	0,816	Valid
	PEU3	0,814	Valid
	PEU4	0,798	Valid
	PEU5	0,822	Valid
	PEU6	0,772	Valid
Perceived Usefulness	PU1	0,766	Valid
	PU2	0,853	Valid
	PU3	0,807	Valid
	PU4	0,824	Valid
	PU5	0,858	Valid
	PU6	0,724	Valid

Referring to the table displaying outer loading values, it's evident that each variable has an outer loading value exceeding 0.6. This observation allows us to conclude that all variables have successfully demonstrated convergent validity.

Discriminant Validity Test

The examination of discriminant validity occurs during the assessment of cross-loading values between the indicators and the variables. This step aims to confirm that each concept within every variable maintains distinction from other variables. The outcomes of the cross-loading test are displayed below:

Table 8. Cross Loading

Variable	ATU	AU	BI	PEU	PU
ATU1	**0,879**	0,545	0,770	0,604	0,739
ATU2	**0,908**	0,512	0,716	0,689	0,681
ATU3	**0,780**	0,419	0,584	0,600	0,697
ATU4	**0,861**	0,499	0,682	0,762	0,754
AU1	0,316	**0,757**	0,428	0,285	0,317
AU2	0,612	**0,887**	0,681	0,415	0,569
AU3	0,436	**0,814**	0,484	0,362	0,378
BI1	0,656	0,475	**0,859**	0,463	0,482
BI2	0,664	0,696	**0,858**	0,460	0,515
BI3	0,756	0,521	**0,825**	0,622	0,636
BI4	0,630	0,533	**0,851**	0,533	0,477
BI5	0,600	0,501	**0,720**	0,509	0,537
PEU1	0,394	0,212	0,346	**0,666**	0,399
PEU2	0,610	0,312	0,445	**0,816**	0,599
PEU3	0,680	0,349	0,497	**0,814**	0,641
PEU4	0,592	0,400	0,595	**0,798**	0,561
PEU5	0,654	0,259	0,430	**0,822**	0,604
PEU6	0,654	0,501	0,613	**0,772**	0,592
PU1	0,618	0,262	0,387	0,670	**0,766**
PU2	0,668	0,525	0,556	0,577	**0,853**
PU3	0,585	0,456	0,494	0,522	**0,807**
PU4	0,702	0,526	0,579	0,542	**0,824**
PU5	0,774	0,399	0,543	0,642	**0,858**
PU6	0,677	0,430	0,554	0,572	**0,724**

Table above demonstrates that the loading factor values for each variable and its corresponding indicators are the highest in comparison to when those indicators are linked with other variables. This implies that, based on these loading factor values, each variable exhibits robust discriminant validity.

When evaluating discriminant validity, an alternative approach involves comparing the square root of the Average Variance Extracted (AVE). Discriminant validity is deemed adequate when the square root of AVE exceeds the variable correlation value. The AVE and its square root are displayed as follows:

Table 9. AVE

Variable	AVE	Status
ATU	0,737	Valid
AU	0,674	Valid
BI	0,680	Valid
PEU	0,614	Valid
PU	0,651	Valid

Table 10. Square Root of AVE

Variable	ATU	AU	BI	PEU	PU
ATU	**0,858**				
AU	0,577	**0,821**			
BI	0,805	0,667	**0,824**		
PEU	0,775	0,439	0,628	**0,783**	
PU	0,836	0,534	0,644	0,732	**0,807**

Based on the table above show that all variables have a good disciminant validity.

Reliability Test

The reliability assessment is conducted to demonstrate the precision, stability, and consistency of the instrument in gauging a variable. A latent variable is considered to have strong reliability when its Cronbach's alpha and composite reliability values > 0.7 [9].

Table 11. Reliability test

Variable	Cronbach's Alpha	Composite Reliability
ATU	0,880	0,884
AU	0,762	0,813
BI	0,881	0,886
PEU	0,874	0,884
PU	0,892	0,894

Table above indicates that the Cronbach's alpha and composite reliability values for every utilized variable exceed the threshold of 0.70. This suggests that each indicator within the variables demonstrates strong reliability, thus enabling further analysis to proceed.

4. 3 Inner Model Evaluation

Inner model evaluation is useful for describing how the relationships between latent variables formed based on the substance of the theory relate to each other. The assessment of the structural model is evident in the associations between latent variables. These connections between constructs become apparent by examining the significance of the R-squared values for each particular exogenous latent variable concerning the endogenous variables.

Coefficient of Determination R-Square

Structural model testing can be seen from the r-square value which is a goodness-fit model test. The r-square value can be categorized as strong if it is 0.75, moderate 0.50, and weak 0.25 [9]. The results of testing the inner model on r-square are shown in the following table:

Table 13. R-Square

Variable	R-Square
ATU	0,757
AU	0,445
BI	0,648
PU	0,536

Table above shows that the r-square value on ATU is 0.757. This means that PU and PEU are able to explain ATU by 75.7%, and the rest is explained by other factors. The r-square value on AU is 0.445, which means that BI is able to explain AU by 44.5% and the rest is explained by other factors. The r-square value on BI is 0.648, which means that ATU is able to explain BI by 64.8% and the rest is explained by other factors. The r-square value on PU is 0.536, which means that PEU is able to explain the PU variable by 53.6% and the rest is explained by other factors.

Hypothesis Test

Hypothesis testing is conducted using the bootstrap method under the condition that the t-statistic value at a 5% significance level (0.05) is greater than 1.96 and has a p-value less than 0.05, signifying the acceptance of the hypothesis [9]. The ensuing outcomes represent the path coefficients computed with SmartPLS 4.0.

Table 14. Path Coefficient

Variable	Original Sample	T Statistics	P values
ATU -> BI	0,805	17,874	0
BI -> AU	0,667	10,906	0
PEU -> ATU	0,351	3,686	0
PEU -> PU	0,732	13,963	0
PU -> ATU	0,58	6,77	0

The results of hypothesis testing based on the path coefficient results are described as follows:

1. Hypothesis 1: PEU has a positive and significant effect on PU in using LinkedIn Learning at PT Semiconductor Batam.

Hypothesis testing displays the t-statistic value of PEU on PU is 13.963> 1.96 and has a p-value of 0.000 <0.05, so it can be said that **Hypothesis 1 is accepted.** The results of this analysis also agree with previous studies, namely Fecira & Abdullah (2020), Rio Jumardi (2020), Mailizar, et al. (2021), Teoh & Tan (2020), and Natasia, et al. (2022) which show that the two variables are strongly related to each other. The resulting positive influence based on the questionnaire question indicators on the PEU variable, namely, users feel that accessing LinkedIn Learning is easy to understand, the learning material on LinkedIn Learning is clear to understand, the language and features available are easy to understand and use, interactive learning material, and the steps in using LinkedIn Learning are easy to remember. The respondents' input is for the company to maintain and provide more convenience in facilities to access learning on LinkedIn Learning.

2. Hypothesis 2: PU has a positive and significant effect on ATU in using LinkedIn Learning at PT Semiconductor Batam.

Hypothesis testing shows that the t-statistic value of PU on ATU is 6.770> 1.96 and has a p-value of 0.000 <0.05, so it can be said that **Hypothesis 2 is accepted.** The results of this analysis also agree with previous research, namely Fecira & Abdullah (2020), Rio Jumardi (2020), Mailizar, et al, (2021), and Natasia, et al. (2022) which show that the two variables are strongly related to each other. The resulting positive influence based on the questionnaire question indicators on the PU variable, namely, users feel that LinkedIn Learning helps in finding learning materials faster and easier, LinkedIn Learning helps in improving work performance, LinkedIn Learning helps in increasing productivity, LinkedIn Learning helps in increasing work effectiveness, and overall LinkedIn Learning is useful in self-development and competence. The respondents' input related to the perceived usefulness is for the company to do more socialization and introduction of learning materials provided on LinkedIn Learning, as well as providing appropriate learning paths and course recommendations for employees so that LinkedIn Learning can be utilized optimally.

3. Hypothesis 3: PEU has a positive and significant effect on ATU in using LinkedIn Learning at PT Semiconductor Batam.

Hypothesis testing shows the t-statistic value of PEU on ATU is 3.686> 1.96 and has a p-value of 0.000 <0.05, so it can be said that **Hypothesis 3 is accepted.** The results of this analysis also agree with several previous studies, namely Rio Jumardi (2020) and Mailizar, et al. (2021) which show that the two variables are strongly related to each other. The resulting positive effect based on the questionnaire question indicators on the PEU variable, namely, users feel that accessing LinkedIn Learning is easy to understand, the learning material on LinkedIn Learning is clear to understand, the language and features available are easy to understand and use, interactive learning material, and the steps in using LinkedIn Learning are easy to remember. The respondents' input is for the company to maintain and provide more convenience in facilities to access learning on LinkedIn Learning.

4. Hypothesis 4: ATU has a positive and significant effect on BI in using LinkedIn Learning at PT Semiconductor Batam.

Hypothesis testing shows that the t-statistic value of ATU on BI is 17.874> 1.96 and has a p-value of 0.000 <0.05, so it can be said that **Hypothesis 4 is accepted.** The results of this analysis also agree with several previous studies, namely Rio Jumardi (2020) which shows that the two variables are strongly related to each other. The positive effect generated based on the indicators of the questionnaire questions on the ATU variable, namely, users feel comfortable in accessing learning material on LinkedIn Learning, users feel that the learning material on LinkedIn learning is interesting to learn, using LinkedIn Learning is the right idea for self-development and competence, and overall feeling satisfy in using LinkedIn Learning.

5. Hypothesis 5: BI has a positive and significant effect on AU using LinkedIn Learning at PT Semiconductor Batam.

Hypothesis testing shows that the t-statistic value of BI on AU is 10.906> 1.96 and has a p-value of 0.000 <0.05, so it can be said that **Hypothesis 5 is accepted.** The results of this analysis also agree with several previous studies, namely Rio Jumardi (2020) and Natasia, et al (2022) which show that the two variables are strongly related to each other. The resulting positive effect is based on the indicators contained in the questionnaire questions on the BI variable, namely, users will try to maximize the use of LinkedIn Learning by using it regularly, plan to continue using LinkedIn Learning as often as possible, plan to continue using LinkedIn Learning for self-development, intend to continue using LinkedIn Learning in the future, and will recommend others to use LinkedIn Learning for self-development.

The conclusion of the hypothesis test in this study can be concluded as follows:

Table 15: Conclusion of Hypothesis Testing

H	Hypothesis	Conclusion
H1	PEU--> PU	Accepted
H2	PU --> ATU	Accepted
H3	PEU --> ATU	Accepted
H4	ATU --> BI	Accepted
H5	BI --> AU	Accepted

5 Conclusions and Suggestions

5.1 Conclusion

Below are the conclusions based on the analysis and discussion in this research as follows:

1. Perceived Ease of Use (PEU) has a positive and significant effect on Perceived Usefulness (PU) in using LinkedIn Learning at PT Semiconductor Batam. Based on this, it means that the better PEU by LinkedIn Learning users, the PU by users will also increase.
2. Perceived Usefulness (PU) has a positive and significant effect on Attitude Towards Using (ATU) in the use of LinkedIn Learning at PT Semiconductor Batam. Based on this, it means that the better the PU in using LinkedIn Learning, the ATU by users will also increase.
3. Perceived Ease of Use (PEU) has a positive and significant effect on Attitude Towards Using (ATU) in the use of LinkedIn Learning at PT Semiconductor Batam. Based on this, it means that the better PEU by users, the ATU by user will also increase.
4. Attitude Towards Using (ATU) has a positive and significant effect on Behavioral Intention (BI) in using LinkedIn Learning at PT Semiconductor Batam. Based on this, it means that the better ATU by users, the BI by user will also increase.
5. Behavioral Intention (BI) has a positive and significant effect on Actual Usage (AU) in using LinkedIn Learning at PT Semiconductor Batam. Based on this, it means that the better BI by users, the AU by user will also increase.

5.2 Suggestions

Suggestions and inputs for PT Semiconductor Batam in this research are as follows:

1. Company are expected to be able to maintain and improve the provision of facilities in accessing LinkedIn Learning, such as paying attention to the company's computer facilities and adequate Kiosk stations, so that LinkedIn Learning can be utilized by both shopfloor and non-shopfloor employees in accessing LinkedIn Learning.
2. Company are expected to be more active in attracting employee interest in utilizing LinkedIn Learning, this can be done by routinely conducting socialization or introductions related to learning materials provided on LinkedIn Learning, as well as providing appropriate learning paths and course recommendations to employees so that employees are able to optimally utilize LinkedIn Learning as a medium for self-development and competency improvement.
3. Company are expected to conduct monitoring and evaluation to ensure that employees are able to take the time to be able to carry out self-development independently by utilizing the LinkedIn Learning facilities provided by the company.

Reference

[1] I. Permatasari and H. Hardiyan, “Pengaruh E-learning sebagai media pelatihan dan pengembangan terhadap kinerja karyawan BCA KCU Tangerang,” Jurnal Sisfokom (Sistem Informasi Dan Komputer), vol. 7, no. 1, pp. 1–8, 2018.

[2] A. B. Hakim, “Efektifitas penggunaan e-learning moodle, google classroom dan edmodo,” Jurnal I-Statement, vol. 2, no. 1, pp. 1–6, 2016.

[3] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly,* vol. 13, no. 3, pp. 319-340, 1989, doi: 10.2307/249008.

[4] I. Maita and S. Majid, “Analisis Penerimaan terhadap Penggunaan E-Learning Menggunakan Metode Technology Acceptance Model (TAM),” Jurnal Sistim Informasi dan Teknologi, pp. 30–35, 2022.

[5] R. Jumardi, “Evaluasi E-Learning menggunakan pendekatan technology acceptance model,” J. Technopreneursh. Inf. Syst, vol. 3, no. 2, pp. 34–41, 2020.

[6] S. Silahuddin, “Penerapan e-learning dalam inovasi pendidikan,” CIRCUIT: Jurnal Ilmiah Pendidikan Teknik Elektro, vol. 1, no. 1, 2015.

[7] H. D. Surjono, "The design of adaptive e-learning system based on student's learning styles," *International Journal of Computer Science and Information Technologies*, vol. 2, no. 5, pp. 2350-2353, 2011.

[8] R. A. Noe, M. J. Tews, and A. McConnell Dachner, "Learner engagement: A new perspective for enhancing our understanding of learner motivation and workplace learning," *Acad Manag Ann*, vol. 4, no. 1, pp. 279-315, 2010.

[9] I. Ghozali and H. Latan, “Partial least squares konsep, teknik dan aplikasi menggunakan program smartpls 3.0 untuk penelitian empiris,” Semarang: Badan Penerbit UNDIP, 2015.

[10] A. P. Teoh and Y. S. Tan, "Predicting behavioral intention of manufacturing engineers in Malaysia to use e-learning in the workplace," *International Review of Research in Open and Distributed Learning*, vol. 21, no. 4, pp. 20-38, 2020.

[11] S. R. Natasia, Y. T. Wiranti, and A. Parastika, "Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach," *Procedia Comput Sci*, vol. 197, pp. 512-520, 2022.

[12] M. Mailizar, D. Burg, and S. Maulina, "Examining university students' behavioral intention to use e-learning during the COVID-19 pandemic: An extended TAM model," *Educ Inf Technol (Dordr)*, vol. 26, no. 6, pp. 7057-7077, 2022.