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EVALUATING USER ACCEPTANCE TOWARDS DIGITAL COMPETENCY ASSESSMENT IN HIGHER EDUCATIONAL INSTITUTIONS

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Abstract. *User acceptance of recent technology depends on many factors. This study examines the acceptance and the use of digital competency assessment using the Unified Theory on Acceptance and Use of Technology (UTAUT) approach in a diverse environment of a well-known private academic institution. The uniqueness of this study is that there is enforcement from the institution to use the system, while the UTAUT model mentioned Voluntariness of Use moderates Performance Expectancy, Effort Expectancy, and Social Influence on Behavioral Intention. One hundred and eighty-five respondents were involved in this study from staff to director level. This study examines Job Level as a new moderator on the relationship between other variables tested in this study. The result found out that Job Level did not moderate the relationship between variables.*
Keywords: User Behavior, Competency assessment, Job Level, Technology acceptance, UTAUT

1. **Introduction.** Digitalization is not an option for academic institutions during this coronavirus pandemic, the digital transformation must occur as the education sector is heavily affected. For example, institutions are conducting online classes using an Internet connection. This transformation works best when implemented throughout the organization, not only for the learning activities but the whole process. Digital transformation can increase satisfaction, and improve speed and transparency [1].

This study takes place in a private academic institution in Indonesia that is well-known for its computer studies. The institution provides learning from early childhood education up until doctoral degrees. Recently, the institution achieved a 5-stars QS World University Ranking. One of the digital transformations in this institution is digitizing the competency assessment process for each of its employees. Currently, the institution is implementing seven Job Levels to run its operations.

The digital competency assessment implemented in the institution is Synergo, a part of the Human Resources Management (HRM) system, and accessible through web browsers. A study by Al-Ajlouni et al. stated that user acceptance of HRM systems is a critical factor in performance effectiveness and cost reduction [2].

Synergo is a cloud-based messaging, collaboration, and workflow management software accessible through web browsers or mobile applications. However, the current implementation in the institution is only for competency assessment, and the access is opened only through a web browser for security purposes.

The assessment model is 360-degree; each employee must assess the competencies for peers, direct supervisor, and direct subordinates within the yearly assessment period. The

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aggregated value will then be combined with the Key Performance Indicator (KPI) value through a 9-box talent matrix to get the final result. The result will then be used for other processes, such as development programs, job movement, and salary increment factor. The current 360-degree assessment weighed more on the immediate supervisor and the second-level supervisor; this means the higher Job Level has a higher evaluation responsibility. This study examines the acceptance and use of digital competency assessment using a modified UTAUT model by checking if Job Level moderates determinants on Behavioral Intention and Use Behavior.

Although users only needed to assess once in a yearly period, the assessment can be done anytime throughout the year from a web browser. Interestingly, many users only log into the system near the due date, in January. This fact also shows that the number only increased significantly when near the due dates, which usually fall in January or early February (see Figure 1).

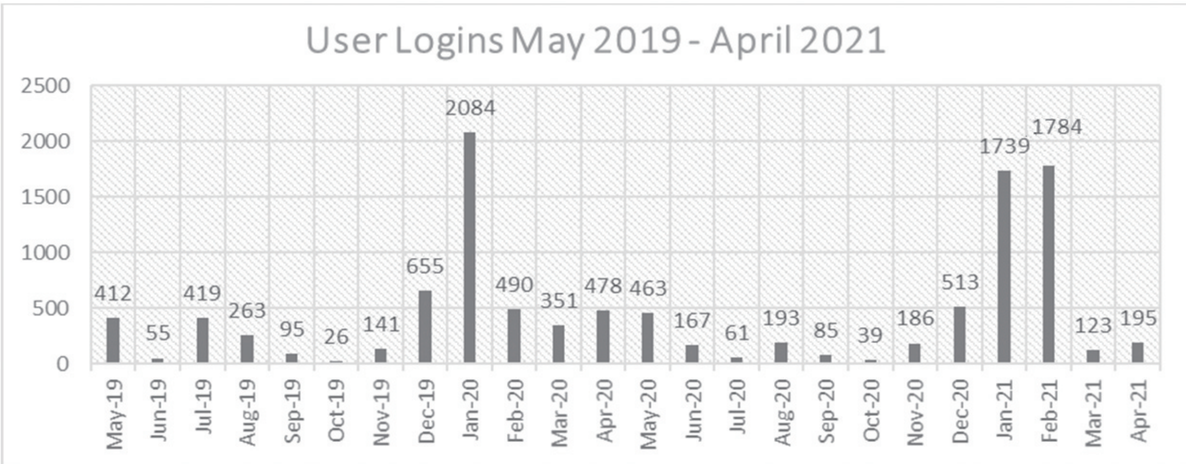

Figure 1. Number of user logins (Source: Internal Data)

Researchers have been conducting studies in different organizations using different technologies at various locations, distinct roles, and mechanisms. Some studies in the academic field also take place, such as "Evaluating Students' Acceptance and Use of Tablet PCs in Collegiate Classrooms" by El-Gayar & Moran; the result shows that the model is consistent with the UTAUT model [3]. Another study by Pynoo et al., "Predicting Secondary School Teachers' Acceptance and Use of a Digital Learning Environment: A Cross-Sectional Study", proposed that to maximize the use of a digital learning environment, its usefulness should be demonstrated and stressed, while school management should enforce teachers to use the Digital Learning Environment (DLE) [4].

The uniqueness of this study is that there is enforcement from the institution to use the system, as previously suggested for future studies by Pynoo et al. [4]. While one of the moderating variables introduced in the original UTAUT model involves free will through Voluntariness of Use which moderates the determinants on Behavioral Intention [5]. Will enforcement in using the system still make the model consistent with the original technology acceptance model, the UTAUT?

2. **Literature Review.** A comparison study between the Technology Acceptance Model (TAM) and UTAUT on determinants of computer usage among educators by Ling et al. proposed that UTAUT is more suitable to be used among educators [6]. Thus, this study uses the UTAUT model by Venkatesh et al.

Venkatesh et al. proposed a unified model (see Figure 2) on acceptance and the use of technology with four determinants of intention and usage: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) and up

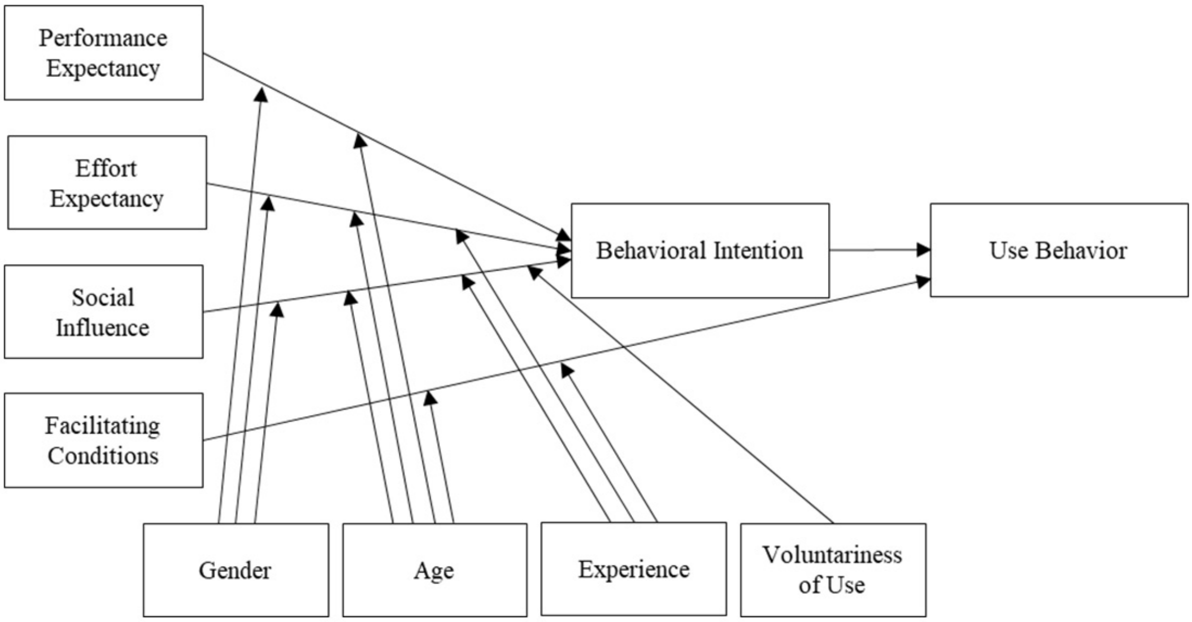

FIGURE 2. UTAUT model proposed by Venkatesh et al.

to four moderators of key relationships (i.e., Gender, Age, Experience, and Voluntariness of Use) [7].

2.1. **Direct effect.** The UTAUT model proposed positive and significant effects from Performance Expectancy, Effort Expectancy, and Social Influence on Behavioral Intention [7]. The present study hypothesized that PE, EE, and SI could significantly influence users' BI toward accepting and adopting the system. The following hypotheses were proposed.

H_1: Performance Expectancy has a positive and significant effect on Behavioral Intention

H_2: Effort Expectancy has a positive and significant effect on Behavioral Intention

H_3: Social Influence has a positive and significant effect on Behavioral Intention

Other direct effects proposed are from Facilitating Conditions and Behavioral Intention on Use Behavior. The following hypotheses were proposed.

H_4: Facilitating Conditions has a positive and significant effect on Use Behavior

H_5: Behavioral Intention has a positive and significant effect on Use Behavior

2.2. **Indirect effect.** The UTAUT model also proposed indirect effects through mediating variables of Behavioral Intention on Use Behavior, namely Performance Expectancy, Effort Expectancy, and Social Influence. The following hypotheses were proposed.

H_6: Behavioral Intention mediates Performance Expectancy on Use Behavior

H_7: Behavioral Intention mediates Effort Expectancy on Use Behavior

H_8: Behavioral Intention mediates Social Influence on Use Behavior

2.3. **New moderation mechanism.** In 2016, Venkatesh et al. summarized 858 UTAUT journal papers from September 2003 to December 2014. New exogenous mechanisms, new endogenous mechanisms, new moderation mechanisms, and new outcome mechanisms are proposed [8]. The research outcome is the UTAUT extensions, which cover expansion from the original UTAUT model (see Figure 3).

Job Level can be described as a hierarchical structure of position or designation in an organization. This study proposes to check if it moderates the relationship between the determinants. As UTAUT extensions suggest introducing new moderation mechanisms,

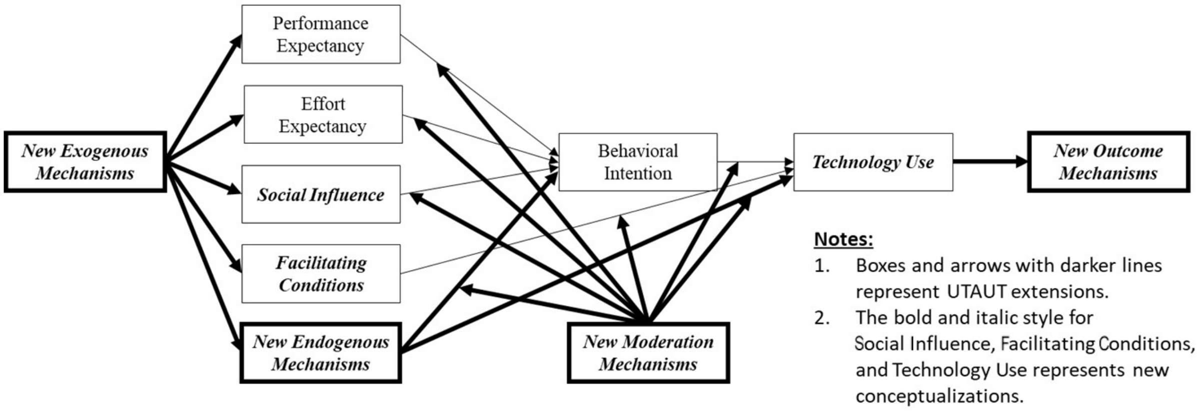

FIGURE 3. UTAUT extensions

this study proposed Job Level as the new moderation mechanism. It has a high impact on the assessment process. The following hypotheses were proposed.

H_9: The relationship between Performance Expectancy and Behavioral Intention is moderated by Job Level

H_{10}: The relationship between Effort Expectancy on Behavioral Intention is moderated by Job Level

H_{11}: The relationship between Social Influence on Behavioral Intention is moderated by Job Level

H_{12}: The relationship between Facilitating Conditions on Use Behavior is moderated by Job Level

H_{13}: The relationship between Behavioral Intention on Use Behavior is moderated by Job Level

Based on the hypotheses aforementioned, the model proposed is presented in Figure 4 below.

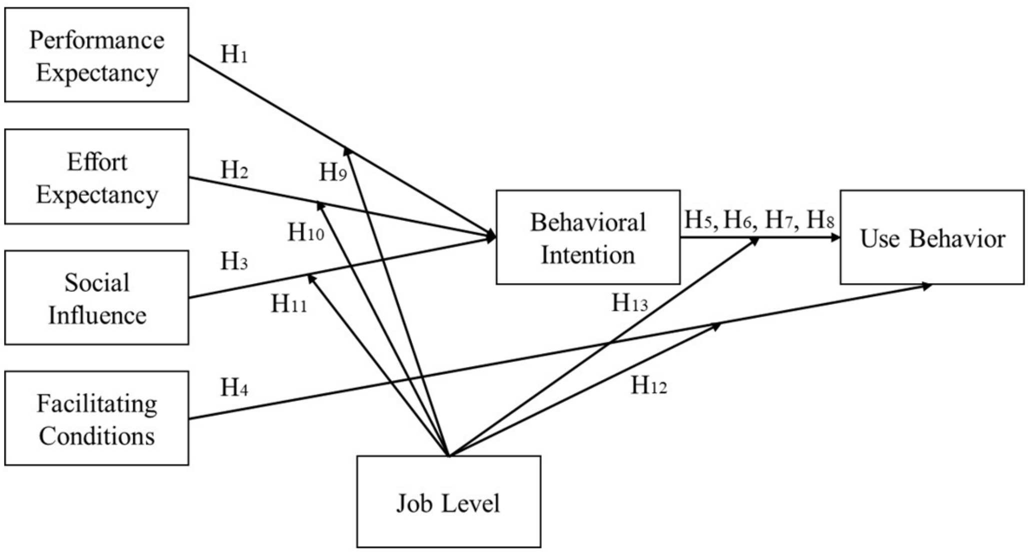

FIGURE 4. Proposed UTAUT model

3. **Methodology.** This research used survey results as the primary data source with 185 respondents, consisting of 82 males or 44.3% and 103 females or 55.7%. The demographics of the respondents are shown in Table 1.

This research method uses the Partial Least Squares (PLS) technique through Smart-PLS 3 software [9]. Partial Least Squares Structural Equation Modeling (PLS-SEM) has

Table 1. Respondent profile

Job Level	Respondent	Age	Respondent	Service years	Respondent
Staff	39 (21.08%)	0-25	12 (6.49%)	0-5	63 (34.05%)
Officer	39 (21.08%)	25-30	30 (16.22%)	6-10	38 (20.54%)
Supervisor	50 (27.03%)	31-35	41 (22.16%)	11-15	31 (16.76%)
Manager	43 (23.24%)	36-40	36 (19.46%)	16-20	36 (19.46%)
Senior Mgr.	8 (4.33%)	41-56	62 (33.51%)	21-25	11 (5.95%)
General Mgr.	3 (1.62%)	> 56	4 (2.16%)	> 25	6 (3.24%)
Director	3 (1.62%)				

become a critical multivariate analysis technique that HRM researchers frequently use [10]. It is a causal-predictive approach to SEM that emphasizes prediction in estimating statistical models, whose structures are designed to provide causal explanations [11].

This research used quantitative research through an anonymous survey questionnaire consisting of 21 survey items about Performance Expectancy (PE01-PE03), Effort Expectancy (EE01-EE04), Social Influence (SI01-SI04), Facilitating Conditions (FC01-FC 04), Behavioral Intention (BI01-BI03), and Use Behavior (UB01-UB03) using 6-point Likert scale. The Likert scale is one of the most reliable ways to measure perceptions, opinions, and behaviors. It is commonly used in survey research using primary and secondary data to measure the respondents' attitudes by asking how they agree or disagree with a particular question [12]. The respondent is also required to choose their current Job Level. The options are Staff, Officer, Supervisor, Manager, Senior Manager, General Manager, Director with the value of 1 to 7, respectively.

The minimum sample size for SEM should be ten times the maximum number of arrowheads pointing at a latent variable anywhere in the PLS path model, according to Hair et al. [13]. Based on the guidelines, the minimum sample size for this study is $10 \times 12 = 120$ respondents. The survey has 185 responses with complete answers. All responses were processed into SmartPLS, and the bootstrapping result can be seen in Figure 5.

The outer model was validated using convergent and discriminant validity tests. The convergent validity test shows that some indicators have outer loading values less than 0.708. Observed variables EE02, EE03, SI02, and UB01 were removed as proposed by Hair et al. [13]. In contrast, the other two observed variables, FC03 and PE03, were kept as when an outer loading is between 0.4 and 0.7, the decision on whether to keep or delete the item depends on the (high) outer loadings of the other items and the results of criteria such as composite reliability and convergent validity as stated by Avkiran & Ringle [14]. Chin also stated that the Average Variance Extracted (AVE) should be above 0.50 [15], and the current AVE values are above 0.5. The discriminant validity tests were passed for both Fornell-Larcker criterion values and cross loadings values. The reliability test for the outer model was passed using the composite reliability test, as all values are above cut-off values of 0.7.

Cronbach's Alpha and rho_A values show that all values are above 0.7 except for UB. However, UB's composite reliability was passed with the value of 0.854. When analyzing and assessing the measures' internal consistency reliability, the composite reliability represented the upper bound while Cronbach's Alpha represented the lower bound [13]; thus, these valid and reliable indicators were used.

The model fit test with an SRMR value of 0.082 was passed with the value below 0.1, and the Chi^2 value of 584.042 is above 0.9. The Normed Fit Index (NFI) value of 0.697 shows that 69.7% of the model is better than the null model.

The f^2 values show Job Level as the moderating variable is weak to moderate Performance Expectancy, Effort Expectancy, and Social Influence on Behavioral Intention, neither Facilitating Conditions and Behavioral Intention on Use Behavior. The strong f^2

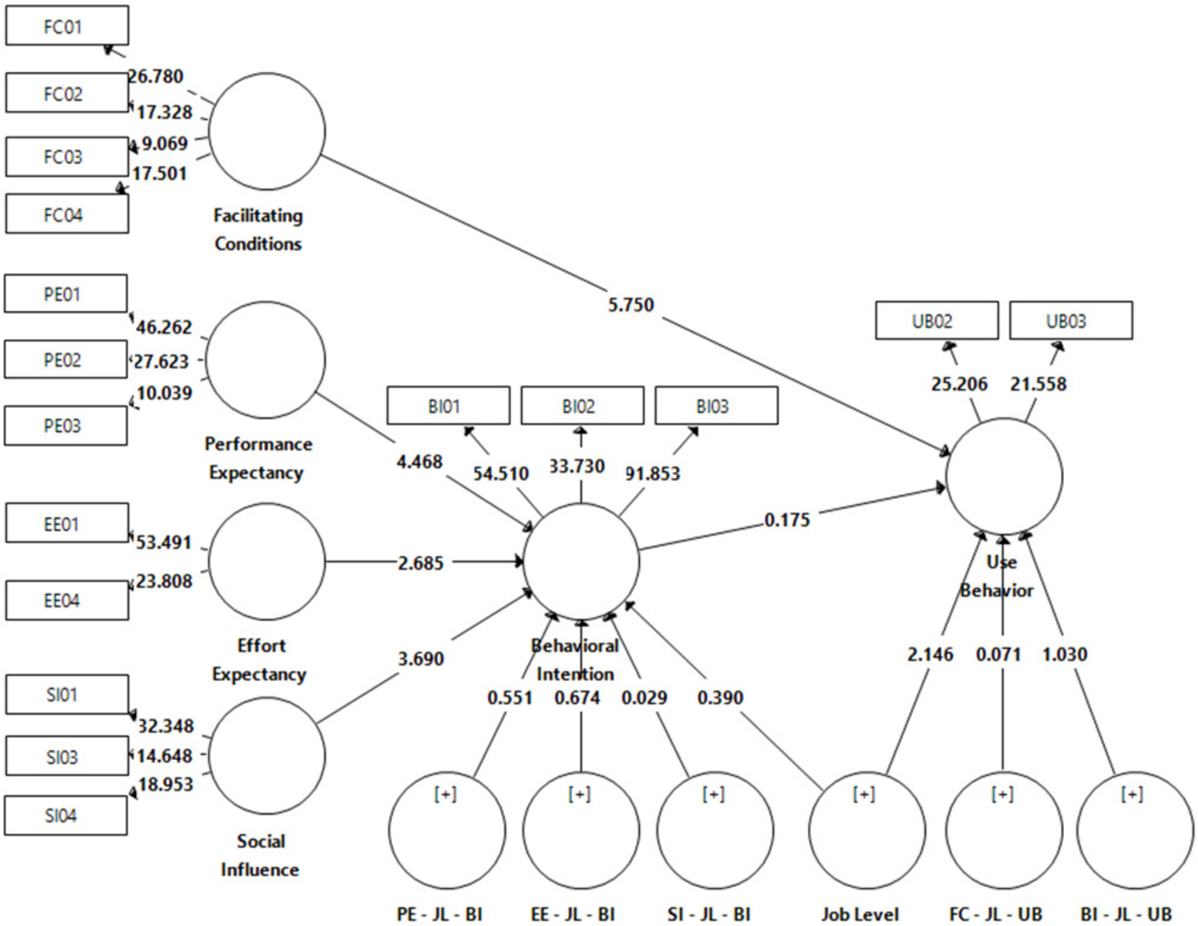

FIGURE 5. Proposed UTAUT model in SmartPLS 3 after bootstrapping

value is only found on Facilitating Conditions on Use Behavior (FC $\to$ UB) = 0.205 as stated by Cohen through Hair et al. f^2 are that values of 0.02, 0.15, and 0.35 respectively, represent small, medium, and significant effects [13,16].

All inner Variance Inflation Factor (VIF) values show no collinearity issues, and all values shown are below 5 [13]. As with multiple regression, the adjusted coefficient of determination (R Adjusted^2) can be used as the criterion to avoid bias toward complex models [13]. R Adjusted^2 values show Behavioral Intention value of 53.3% and Use Behavior value of 26.2%.

The Q^2, with blindfolding omission distance = 7, shows that Behavioral Intention and Use Behavior are valid as the dependent variables (BI = 0.456, UB = 0.185) as all values are above 0. Q^2 values larger than 0 suggest that the model has predictive relevance for a specific endogenous construct. In contrast, values of 0 and below indicate a lack of predictive relevance [13].

4. **Result and Discussion.** The Bootstrapping result through SmartPLS 3 for 5,000 samples is presented in Table 2.

The table shows that Performance Expectancy positively and significantly affects Behavioral Intention with P values = 0.000. Effort Expectancy and Social Influence also positively and significantly affect Behavioral Intention. Thus, H_1, H_2, and H_3 are accepted and consistent with the original UTAUT model.

Facilitating Conditions also have a positive and significant effect on Use Behavior. The f^2 also shows this determinant plays a significant role in the Use Behavior ($f^2 = 0.205$). The institution can pay more focus on this area as the first step to increase the Use Behavior.

TABLE 2. Bootstrapping result

Hypotheses	**Original sample**	**T statistics**	**P values**	f^2
H_1: PE $\rightarrow$ BI	0.373	4.468	0.000	0.133
H_2: EE $\rightarrow$ BI	0.192	2.685	0.007	0.045
H_3: SI $\rightarrow$ BI	0.304	3.690	0.000	0.124
H_4: FC $\rightarrow$ UB	0.502	5.750	0.000	0.205
H_5: BI $\rightarrow$ UB	−0.014	0.175	0.861	0.000
H_6: PE $\rightarrow$ BI $\rightarrow$ UB	−0.005	0.174	0.862	–
H_7: EE $\rightarrow$ BI $\rightarrow$ UB	−0.003	0.158	0.875	–
H_8: SI $\rightarrow$ BI $\rightarrow$ UB	−0.004	0.166	0.868	–
H_9: JL $\rightarrow$ (PE $\rightarrow$ BI)	0.050	0.551	0.582	0.002
H_{10}: JL $\rightarrow$ (EE $\rightarrow$ BI)	−0.050	0.674	0.501	0.003
H_{11}: JL $\rightarrow$ (SI $\rightarrow$ BI)	−0.002	0.029	0.977	0.000
H_{12}: JL $\rightarrow$ (BI $\rightarrow$ UB)	−0.106	1.030	0.303	0.007
H_{13}: JL $\rightarrow$ (FC $\rightarrow$ UB)	0.007	0.071	0.943	0.000

Behavior Intention did not have an effect on Use Behavior with P value = 0.861 far above 0.05. The hypothesis H_5 is rejected. It also did not successfully mediate Performance Expectancy, Effort Expectancy, and Social Influence on Use Behavior; all P values are above 0.05. Thus, hypotheses H_6, H_7, and H_8 are rejected.

The Job Level also did not successfully moderate Performance Expectancy, Effort Expectancy, and Social Influence on Behavioral Intention and Facilitating Conditions and Behavioral Intention on Use Behavior; all P values are above 0.05. Thus, hypotheses H_9-H_{13} are rejected.

In summary, the three determinants that positively and significantly affect Behavioral Intention are Performance Expectancy, Effort Expectancy, and Social Influence.

Facilitating Conditions is found out to be the most significant factor giving impact to the Use Behavior. Providing support in terms of IT infrastructure to support the Facilitating Conditions would improve the Use Behavior. Performance Expectancy is found out to be the key factor having an impact on Behavioral Intention.

The result also shows that Job Level does not moderate the relationship between determinants. Diversified respondents could be one of the factors causing it. Job Level might have a moderation effect if applied in a more specific function/work unit.

5. **Conclusions.** The institution can make the system more useful by adding more functions and features to improve work performance. Implementing the mobile application will add a new channel to access the system, which will make it easier to access the system. Producing more change agents could be one option to increase the social influence, which could make the system usage higher. Enabling more functions or features in the system will maximize the user's intention to use the system.

The current study found that the result is not consistent with the original UTAUT design. And this study proves the suggestion by Pynoo et al. that enforcement did not increase the Use Behavior.

Future studies can further check the significance of enforcement to the Behavioral Intention and Use Behavior and consider using another acceptance model. Having non-diversified respondents would reduce bias in responses. The use of Multigroup Analysis (MGA) is advised for diversified respondents. Adding more moderation mechanisms such as Education Background and using a larger Likert scale (e.g., 10-point scale) would enrich the analysis in the academic field. And compare between acceptance in a free-will app with enforcement app using the same respondents.

REFERENCES

[1] I. Mergel, N. Edelmann and N. Haug, Defining digital transformation: Results from expert interviews, *Gov. Inf. Q.*, DOI: 10.1016/j.giq.2019.06.002, 2019.

[2] M. I. Al-Ajlouni, S. Nawafleh, H. Alsari, M. N. Almarshad and R. Tbaishat, Determinants of user acceptance of electronic-HRM through the extension of UTAUT model via the structural equation modelling approach, *J. Inf. Knowl. Manag.*, DOI: 10.1142/S0219649219500448, 2019.

[3] O. F. El-Gayar and M. Moran, Evaluating students' acceptance and use of tablet PCs in collegiate classrooms, *The 13th Americas Conference on Information Systems (AMCIS2007)*, Keystone, Co, USA, 2007.

[4] B. Pynoo, P. Devolder, J. Tondeur, J. Van Braak, W. Duyck and P. Duyck, Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study, *Comput. Human Behav.*, DOI: 10.1016/j.chb.2010.10.005, 2011.

[5] G. C. Moore and I. Benbasat, Development of an instrument to measure the perceptions of adopting an information technology innovation, *Inf. Syst. Res.*, DOI: 10.1287/isre.2.3.192, 1991.

[6] L. W. Ling, A. G. Downe, W. F. W. Ahmad and T. T. Lai, Determinants of computer usage among educators: A comparison between the UTAUT and TAM models, *National Postgraduate Conference*, pp.1-6, DOI: 10.1109/NatPC.2011.6136322, 2011.

[7] V. Venkatesh, M. G. Morris, G. B. Davis and F. D. Davis, User acceptance of information technology: Toward a unified view, *MIS Q. Manag. Inf. Syst.*, DOI: 10.2307/30036540, 2003.

[8] V. Venkatesh, J. Y. L. Thong and X. Xu, Unified theory of acceptance and use of technology: A synthesis and the road ahead, *J. Assoc. Inf. Syst.*, DOI: 10.17705/1jais.00428, 2016.

[9] C. M. Ringle, S. Wende and J.-M. Becker, *SmartPLS 3*, SmartPLS GmbH, Bönningstedt, 2015.

[10] C. M. Ringle, M. Sarstedt, R. Mitchell and S. P. Gudergan, Partial least squares structural equation modeling in HRM research, *Int. J. Hum. Resour. Manag.*, DOI: 10.1080/09585192.2017.1416655, 2020.

[11] M. Sarstedt, C. M. Ringle and J. F. Hair, Treating unobserved heterogeneity in PLS-SEM: A multi-method approach, in *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications*, H. Latan and R. Noonan (eds.), Springer International Publishing AG, 2017.

[12] Z. Awang, A. Afthanorhan and M. Mustafa, The Likert scale analysis using parametric based Structural Equation Modeling (SEM), *Comput. Methods Soc. Sci.*, vol.4, no.1, pp.13-21, DOI: 10.5281/zenodo.1299429, 2016.

[13] J. F. Hair, G. T. M. Hult, C. M. Ringle and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd Edition, SAGE, 2017.

[14] N. K. Avkiran and C. M. Ringle, *Partial Least Squares Structural Equation Modeling: Recent Advances in Banking and Finance*, Springer, 2018.

[15] W. W. Chin, How to write up and report PLS analyses, in *Handbook of Partial Least Squares. Springer Handbooks of Computational Statistics*, V. Esposito Vinzi, W. Chin, J. Henseler and H. Wang (eds.), Berlin, Heidelberg, Springer, 2010.

[16] J. Cohen, *Statistical Power Analysis for the Behavioural Sciences*, Hillside, Lawrence Earlbaum Associates, NJ, 1988.