E-learning Acceptance Model in a Pandemic Period with an expansion to the Quality Work-Life and IT Self Efficacy Aspects

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Abstract—This study was inspired by the COVID-19 pandemic, which affected face-to-face learning, leading to the e-learning system. The learning system that was originally done face-to-face was forced to go online. Educational institutions and related parties are not prepared for this sudden change. So it is interesting to research the intentions of students related to learning during this pandemic in the framework of the technology acceptance model. Specifically, it aimed to analyze the acceptance and satisfaction model of e-learning users amid the pandemic. The proposed model that predicts student intentions and satisfaction with e-learning is an expanded Technology Acceptance Model with work-life quality factors and information technology self-efficacy. This research will provide empirical evidence related to the dimensions of quality work-balance and the ability to use information technology related to e-learning access, in addition to other factors in the technology acceptance model. The data was collected using online questionnaires with a snowball sampling model. The sample included students from various Indonesian universities voluntarily filling out the questionnaires. The structural equation model processed the data using a Partial Least Square (PLS) approach and analyzed it through the SmartPLS3 program. The results showed that the variables of quality of work life and self-efficacy of information technology such as computers, internet, and communication can explain the acceptance of e-learning models, especially during a pandemic. As an implication of the results of this study shows that teachers should focus on e-learning designs that facilitate access to lecture material and student-teacher interactions in order to attract intentions and increase student satisfaction in using e-learning.

Index Terms—E-Learning, Acceptance Model, Work Life Balance, IT Self-Efficacy, User Satisfaction

I. INTRODUCTION

The pandemic that hit the world at the end of 2019 has disrupted conventional learning systems face-to-face [1–5]. Educational institutions are forced to shift the learning system to online. Although e-learning is not new in the world of education, the conditions of sudden change will have an impact on all relevant entities [1, 2, 4, 6, 7]. Therefore, this study aims to review behavioral intention factors and user satisfaction in e-learning during a pandemic using the expanded TAM framework.

Nowadays, information and communication technology development has promoted educational institutions’ innovations in the learning process. E-learning is an alternative that covers a wider audience and overcomes distance barriers. Furthermore, it is essential during the COVID-19 pandemic [1, 7–9]. Therefore, the student’s perception of e-learning supports the academic program’s effectiveness. The e-learning user’s attitude determines the effectiveness of the learning process [2–4, 10].

The learning system has drastically changed due to the pandemic that restricted face-to-face engagements in various sectors, including education. Conventional classroom lectures shifted to online-based learning through various intermediary tools [1, 2, 4, 8, 9]. Educational institutions had not anticipated this situation, hence the immediate policy implementations. Online learning depends on the teachers’ readiness and infrastructure availability. Consequently, the application of e-learning involves technological issues, social conditions, and behavior [3, 5, 8, 9, 11–13]. The online learning system also lacks student-teacher direct interactions compared to classroom learning [3, 14].

This study analyzed students’ perceptions of online learning systems amid the pandemic, determine factors of acceptance and satisfaction level, and the challenges. Therefore, social factors like quality work-life [11–13, 15–18] and information technology utilization (IT), such as IT self efficacy [5, 19, 20], were included in the Technology Acceptance Model (TAM) as acceptance.
and satisfaction determinants on e-learning.

Most previous studies on e-learning applied different methods, but the Technology Acceptance Model (TAM) was mainly used. TAM is the ideal model to explain the students’ technology acceptance for online learning [11]. It explains the intention and behavior of applying technology influenced by perceived usefulness and ease of use [11, 13, 21]. Various previous studies that applied the TAM model in e-learning were expanded, for example, [11] that examined the TAM expansion in e-learning through social, organizational, and individual factors. The researcher applied the extended TAM model to examine the acceptance of e-learning in Lebanon by including social norms and quality work-life factors. The results showed that all the research factors, namely perceived usefulness, perceived ease of use, social norms, and quality work-life are determinants of students’ behavioral intention [11]. These results supported the previous study conducted [11] on UK university students that perceived ease of use, perceived usefulness, social norms, quality work-life, computer self-efficacy, and facilitating conditions determine acceptance level of e-learning. Quality work-life measure is the strongest and significant determining factor of user acceptance level on e-learning [17, 22]. Tarhini et al. [11, 13] expanded the study by comparing Lebanon and England students with similar factors and found the consistent determinants of acceptance and behavior on e-learning as previously studied.

Siron et al. [14] surveyed 250 students from various Indonesian universities with a different TAM approach, namely perceived enjoyment, student experience, computer anxiety, and perceived self-efficacy factors. It provided empirical evidence on factors of students’ intention to use e-learning. This study applied a different perspective [14], emphasizing quality work-life and IT self-efficiency, besides perceived usefulness, behavioral beliefs, and perceived difficulty factors.

Although research in the field of Technology Acceptance Model in the domain of e-learning has been applied, there is still an opportunity to conduct further studies, especially related to the integration between technology and student welfare in predicting the level of acceptance and satisfaction using e-learning. Previous studies [11, 13, 18, 22] have accommodated quality of work life and computer self-efficacy, but have not included internet and online communication capabilities [19].

Despite the variables of this study have been widely researched, but this research model specifically has novelty in problems and models. The issue raised is how students’ intentions towards the learning model in the midst of a pandemic that occurs suddenly.

II. RESEARCH METHOD

In accordance with the research objectives, the study will use the extended TAM framework [11, 13, 18] and the theory of planned behavior (TPB) by Ajzen in 2002. Furthermore, besides the perceived usefulness, quality work-life factors were adopted from Tarhini et al. [11, 13, 18]. The TAM expansion included behavioral belief and perceived difficulty factors by Yang & Tsai [23]. This study considered the e-learning access factors that depend on the internet and computers and IT self-efficacy, including computer, internet, and Online communication [19]. Thus this research model is presented in Fig. 1.

A. Variables Used

Next will be outlined each of the variables used in describing the research model.

Perceived Usefulness (PU). The instrument used to explain perceived usefulness was adapted from Tarhini, Hone and Liu [11, 13, 18]. Tarhini et al. [11, 13, 18] proved that perceived usefulness greatly contributes
to behavioral intention than perceived ease of use. Perceived usefulness is significant in explaining the acceptance behavior of online learning technology. System users select beneficial tools; hence students should know the usefulness of the presented learning content. Quality and updated content meet the students’ expectations of the e-learning system.

The instrument used to explain perceived usefulness was adapted from Tarhini, Hone, and Liu [11, 13, 18]. PU consists of five statements that explain the user’s perception of e-learning which is to accomplish learning tasks more quickly, improve learning performance, make it easier to learn course material, increase learning productivity, and enhance effectiveness in learning.

Behavioral Beliefs (BB) and Perceived Difficulty (PD). The instrument used to explain Behavioral Beliefs and Perceived Difficulty was adapted from Tarhini, Hone, and Liu [11, 13]. Based on the planned behavior theory by Ajzen 2002 [23], behavioral and contextual beliefs and perceived difficulties are functions of perceived behavioral control and intentions. Furthermore, behavioral beliefs are consequences or other attributes. Subjective norms beliefs are related to perceived social pressure. The perceived behavioral control includes the factors that continue or hinder behavior. Perceived difficulty acts as behavioral control of the utilization acceptance of a system. By underpinning this framework, belief, attitude, and intention factors are applied to online learning. Therefore, behavioral beliefs and perceived difficulties on the e-learning acceptance are applied as part of its consequences and perceived learning behavioral control. Yang & Tsai [23] showed a positive relationship between behavioral beliefs and e-learning acceptance. However, the control beliefs relationship is negative, as explained by the perceived difficulty in the e-learning acceptance.

Perceived difficulty measures the e-learning users’ perceptions of ease of use, playfulness, and challenges of tracking online links. Previous studies indicated that the difficulty and ease of internet access affect e-learning acceptance [23]. The instrument used to explain behavioral beliefs, and perceived success was adapted from Yang and Tsai [23].

BB consists of eight statements about preferences for online or conventional learning systems, whether the more online learning the better the learning outcomes, whether online learning will become a trend in the future, taking online learning for a full semester is better if designed with adequate, using online learning causes no distance from lecturers and classmates, online learning makes it possible to know more about my learning style and competence, online learning can make abstract things real with the help of animations or simulations, online learning makes communication better with lecturers and with classmates. PD consists of three statements that explain whether online learning is fun but not helpful in learning, online learning increases the load and Online learning makes you lost and unfocused.

Quality Work-life (QWL)

The instrument used to explain quality work-life was adapted from Tarhini, Hone and Liu [11, 13]. Quality work-life is widely explored in various professional contexts, organizations, and educational institutions [15, 22]. QWL in the technology aspect refers to a user’s unlimited internet access, facilitating increased satisfaction, enjoyment, and personal values on their work [11, 13, 17, 18]. In the e-learning aspect, quality work-life, according to Tarhini, Hone, and Liu [11, 13, 17], is students’ perceptions and beliefs on technology utilization to improve their quality of life, for example, cost savings for material access activities, and e-mail communication with instructors and friends. Tarhini, Hone, and Liu [11, 13] found that QWL is essential in e-learning to describe the benefits of accessing materials and communication facilities in the learning process.

QWL consists of five statements that explain lecture materials accessed online help them have more time to think creatively and have fun, using online learning materials freely helps save money and energy, using online learning provides more opportunities to participate in class, using emails /chat in communicating with friends or groups saves money and energy, overall, online learning helps improve the quality of work.

IT Self Efficacy (ITSE). Caliskan et al.

According to Caliskan et al. [19], the instrument used to explain IT Self Efficacy is divided into three dimensions: computer, internet, and Online Communication. Computer competence explains whether they can easily use the Windows/Mac operating system, can search for electronic file contents on a computer, can solve problems when facing difficulties in using a computer, easily use Ms Office applications, easily use the software applications they need. Internet competence contains statements about being easy to use Web browsers, easily using search engines, being able to download files from the internet to a computer, easily accessing needed information on the internet.

Online communication competence explains that they can use Internet tools to communicate effectively with others, easily ask questions in discussion forums via the internet, can express themselves easily in writing, can seek help using internet tools to get answers, can easily communicate by voice as well as videos via the internet.

Behavioral intention (BI). This variable measured the students’ acceptance or behavioral intention on e-
learning systems amid the pandemic. The instrument used to explain behavioral intention was adapted from Tarhini, Hone, and Liu [11, 13, 18], consists of a statement that if given the opportunity they intend to use the Web-based learning system to download lecture notes and participate in chat rooms to study on the Web, they will use the Web-based learning system in the next semester, planning to use the Web-based learning system frequently for coursework, and other activities in the next semester.

User Satisfaction. This variable measured user satisfaction with online learning activities. The applied instrument consisted of 5 items that assessed user satisfaction, including online lecture materials, interactions with lecturers and classmates, and the applied media. All indicators were measured by 5 Likert scales, where 1 indicates a low score and 5 the highest score.

B. Samples and Analysis Methods

The sample included students from various Indonesian universities voluntarily filling out the questionnaire. The questionnaires were distributed from May to June 2020 through the g-form using snowball sampling. The structural equation model processed the data using a Partial Least Square (PLS) approach and analyzed it through the SmartPLS program.

The tests were conducted in 3 stages, analyzing the measurement/outer, structural/inner models dan Fit Model [24, 25].

C. Measurement/Outer Model

The outer model is an assessment of the validity of the model and the results will show that the latent construct predicts the size on the block better than the size of the other block. The outer model test followed four criteria: 1) measuring the internal consistency reliability with composite reliability criteria > 0.70. 2) Indicator reliability, where the Outer loading value of each indicator should be > 0.708. 3) Convergent validity where the average variance extracted (AVE) should be higher than 0.50. 4) Discriminant Validity is shown by the Construct correlation with measurement items greater than other constructs correlation, or following the Fornell–Larcker criteria that the value of the AVE square root should be greater than the correlation value between other constructs.

D. Structural/Inner Model

Structural models or inner models will be analyzed in 3 ways, namely: 1) Collinearity assessments with VIF of < 5, R2 of 0.75, 0.50, and 0.25 are substantial, moderate, and weak. 2) Predictive accuracy of the PLS path model Q2 Values larger than zero is meaningful, and the values higher than 0.25, and 0.50 depict small, medium, and large. 3) The relationship between constructs or hypothesis tests was based on the significant value of the path coefficients with a significance level of 5% and produced the expected T score greater than 1.96.

E. Fit Model

The measurement and structural model fit were evaluated to provide predictive information for the overall GoF model. The assessment applied the square root of the average communality index and R-Square multiplication. However, the SmartPLS 3.3 commonalities values were not displayed as they were identical to the AVE coefficients. GoF was calculated based on the average AVE coefficients and R-Square, following 0.10 small, 0.25 medium, and 0.36 large criteria.

III. RESULTS AND DISCUSSION

A. Descriptive analysis

The respondents included 147 (33%) males and 301 (67%) female students. 212 (47%) students disagreed on online learning since the COVID-19 pandemic, while 236 (53%) agreed. The most used e-learning applications are summarized in Table I: Zoom, Chat WhatsApp, Google Classrooms, and Ms. Teams.

Table II above shows that students preferred video calls or virtual face-to-face, audio discussions, chatting,

<table>
<thead>
<tr>
<th>Applications</th>
<th>Total</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zoom</td>
<td>249</td>
<td>23.83</td>
</tr>
<tr>
<td>Chat WhatsApp</td>
<td>185</td>
<td>17.70</td>
</tr>
<tr>
<td>Google class room</td>
<td>159</td>
<td>15.22</td>
</tr>
<tr>
<td>MS Teams</td>
<td>127</td>
<td>12.15</td>
</tr>
<tr>
<td>Email</td>
<td>102</td>
<td>9.76</td>
</tr>
<tr>
<td>E-learning/Moodle</td>
<td>83</td>
<td>7.94</td>
</tr>
<tr>
<td>YouTube</td>
<td>45</td>
<td>4.31</td>
</tr>
<tr>
<td>Google Meet</td>
<td>48</td>
<td>4.59</td>
</tr>
<tr>
<td>Facebook</td>
<td>2</td>
<td>0.19</td>
</tr>
<tr>
<td>WebEx</td>
<td>10</td>
<td>0.96</td>
</tr>
<tr>
<td>Skype</td>
<td>25</td>
<td>2.39</td>
</tr>
<tr>
<td>Others</td>
<td>10</td>
<td>0.96</td>
</tr>
<tr>
<td>Totals</td>
<td>1045</td>
<td>100</td>
</tr>
</tbody>
</table>
e-mail, and WhatsApp for the learning process. Then the study found the most students’ obstacles, such as internet network disturbances and audio technical problems on the computer. Other obstacles included unclear material and different comfort from face-to-face learning.

The following shows the general description of each observed variable perception. The student’s perceptions were grouped into three based on the mean score of each indicator, including low, moderate, and high. The conversion score of 5 Likert scales was calculated by \((\frac{5 - 1}{3}) = 1.3\), and the interval scale for low had a score of \(1 < x \leq 2.3\), Moderate at \(2.3 < x \leq 3.6\), and High at \(> 3.6\).

The descriptive analysis of all constructs, as shown in Table III, indicates that the high perception value was IT Self-Efficacy, consisting of Computer, Internet, and Online Communication, while other variables were perceived as moderate.

### B. Confirmatory Factor Analysis

Evaluation of Measurement/Outer Model

The SmartPLS output in Table IV showed that the model has good internal consistency reliability because the composite reliability of all constructs is \(> 0.70\). Similarly, the reliability indicator is good because the value of the Outer loading, as shown in Fig. 2, is overall \(> 0.708\). Table IV showed that the model has good convergent validity, as indicated by the average variance extracted (AVE) \(> 0.50\). Finally, the result indicated that the outer model measurement has good Discriminant Validity because it meets the Fornell–Larcker criterion correlation indicated by the \(\sqrt{AVE}\) value is greater than the correlation between constructs, except for ITSE which is the second order of CSE, ISE, and OSE (see Appendix).

### C. Evaluation of Inner Model/ Structural Model

The structural/inner model equation was evaluated after the outer model measurement obtained an adequate value. This was performed to predict causality between latent variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PU - Perceived Usefulness</td>
<td>2.88</td>
<td>Moderate</td>
</tr>
<tr>
<td>BB - Behavioral Beliefs</td>
<td>2.99</td>
<td>Moderate</td>
</tr>
<tr>
<td>PD - Perceived Difficulty</td>
<td>3.31</td>
<td>Moderate</td>
</tr>
<tr>
<td>PQWL - Quality of Work Life</td>
<td>3.35</td>
<td>Moderate</td>
</tr>
<tr>
<td>BI - Behavior Intention</td>
<td>2.94</td>
<td>Moderate</td>
</tr>
<tr>
<td>SATIS - Satisfaction</td>
<td>3.11</td>
<td>Moderate</td>
</tr>
<tr>
<td>CSE - Computer Self-Efficacy</td>
<td>3.73</td>
<td>High</td>
</tr>
<tr>
<td>ISE - Internet Self-Efficacy</td>
<td>4.21</td>
<td>High</td>
</tr>
<tr>
<td>OSE - Online Communication Self-Efficacy</td>
<td>3.71</td>
<td>High</td>
</tr>
</tbody>
</table>

The SmartPLS output results presented in Table V showed a good collinearity assessment, with a VIF value less than 5. This indicates a lack of multicollinearity in the latent variables. The next process examined the determinants coefficient value (R²), as shown in Figure 1 that OSE, ISE, and CSE have an explanatory value for the endogenous latent variables’ variance. This is substantial because the value of R² 0.75 is greater than 0.75, whereas it is moderate for BI and Satis because each has a value of 0.673 and 0.715. Furthermore, the blindfolding technique assessed the predictive relevance to obtain the cross-validated redundancy value of each construct. The results provided a Q² value greater than 0.5, indicating that all exogenous constructs had great predictive relevance for the endogenous construct.

The outer and inner models’ values showed good results, leading to testing the path coefficient value. The results in Table 7 showed that all the t-value calculations are greater than 1.96 at \((\alpha) = 5\%\) except for the relationship between ITSE and BI.

The Goodness of Fit (GoF) index was evaluated after the structural model testing. The GoF value of 0.755 was obtained with an average AVE of 0.727 and an R-Square value of 0.784. By convention, this model has a large GoF. The SmartPLS output had an SRMR value.
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of 0.081, indicating that the model has a good fit [25].

The study model has good validity, reliability, and fit model. The analysis showed that the acceptance model of e-learning during the COVID-19 pandemic is formed by the PU, BB, PD, and PQWL factors. In contrast, the user satisfaction model is formed by the PU, BB, PD, PQWL, and ITSE. ITSE contributes to user satisfaction but does not affect acceptance of use.

These results indicate that besides BB, and PD, social factors, especially PQWL, can measure e-learning acceptance and satisfaction, except ITSE that only affects user satisfaction. Additionally, the dimensions of ITSE were explained by the ISE, OSE, and CSE factors. The results of the analysis showed the highest user perception value of QWL to Intention. Thus, the results of this study provide empirical support to quality of work life research on students’ intentions in using e-learning.

The analysis showed that the perceived usefulness measure of e-learning could be explained through indicators of improved performance, productivity, learning effectiveness, and the ease of mastering lecture material. The learning system usability can measure user acceptance and satisfaction. Usability perception increases the students’ acceptance and satisfaction of e-learning. This is supported by Tarhini et al. [11, 13] that PU strongly contributes satisfaction of e-learning users. However, PU has no effect on the use intention.

The results showed that behavioral beliefs are explained through indicators related to the belief that e-learning is better than face-to-face with learning design consequences. Learning design controls the user behavior on acceptance and satisfaction. This is similar to the perceived difficulty, negatively affecting user acceptance and satisfaction. The difficulty level in e-learning is measured by playfulness and challenges in tracking online links, reducing user acceptance and satisfaction. Difficult online access reduces playfulness, user acceptance, and satisfaction. This is similar to Yang & Tsai [23] that there is a positive relationship between the behavior belief and acceptance of e-learning and negative for the control belief explained through perceived difficulty and acceptance.

Social aspects such as quality work life (QWL) affect acceptance of e-learning. QWL shows the students’ benefits through unlimited technology access, contributing to their acceptance and satisfaction. This supports previous studies [11, 13, 17], that unrestricted internet access enhances the e-learning user’s satisfaction, enjoyment, and personal values when working. This is similar to Tarhini, Hone, and Liu [11, 13] that QWL is essential in describing user acceptance and satisfaction of e-learning [17].

IT tools also predict user acceptance and satisfaction of e-learning. The results proved that IT efficacy, such as internet access, computers usage, and other communication devices, strongly contributes to e-learning user satisfaction. According to previous studies [11, 19, 20], users’ ability and experience in information technology enhances readiness to use e-learning and leads to satisfaction. Students’ computer experience increases e-learning acceptance.

IV. CONCLUSION

This study wants to answer the problem of how the student acceptance model for e-learning, as well as whether Quality Work-Life and IT Self Efficacy can explain the E-learning acceptance model in the Pandemic Period. In conclusion, the factors affecting user acceptance and satisfaction of e-learning amid the
pandemic are BB, PD, and PQWL. User satisfaction is formed by PU, BB, PD, PQWL, and ITSE. The results of this study support TAM extension on the quality work-life factor proposed by Tarhini et al. [11, 13] which is shown with high explanatory values for student intentions using e-learning. Additionally, the students' obstacles during the learning process include internet network disturbances and computer technical problems like audio. Some students were uncomfortable delivering lecture material and experienced adjustments because virtual ones drastically replaced face-to-face classes. Furthermore, based on Table IV, the ITSE factor had the highest score compared to other constructs. This indicates that students have great IT skills in mastering computers, internet access, and other communication tools during the pandemic. Therefore, IT is not an obstacle for students accessing and supporting e-learning during the pandemic, especially the respondents. The results of this study are also in line with Caliskan et al. [19], where the value of IT Self-efficacy can also indicate the readiness of students to follow learning through e-learning in the pandemic period.

This study provided theoretical contributions that the acceptance of e-learning models includes social elements related to material access benefits and communication through quality work-life and IT self-efficacy measures such as computers, the internet, and other communication tools. Furthermore, practical contributions to e-learning teachers should focus on e-learning design that facilitates access to lecture materials and student-teacher interactions.

However, this study also has limitation including the scope of students as respondents; hence the results should be interpreted only in the sample studied. Therefore, further study should widen the scope of students in other areas besides big cities to acquire consistent results. Based on the constraints expressed by most respondents on network disturbances, digital dividends in various regions or internet infrastructure should be examined.

REFERENCES


**APPENDIX**

The Appendix can be seen in the next page.
TABLE A1
DETERMINANT VALIDITY.

<table>
<thead>
<tr>
<th></th>
<th>BB</th>
<th>BI</th>
<th>CSE*</th>
<th>ISE*</th>
<th>ITSE*</th>
<th>OSE*</th>
<th>PD</th>
<th>PQWL</th>
<th>PU</th>
<th>SATIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB</td>
<td>0.792</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BI</td>
<td>0.767</td>
<td>0.937</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>CSE</td>
<td>0.408</td>
<td>0.36</td>
<td>0.822</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>ESE</td>
<td>0.299</td>
<td>0.278</td>
<td>0.773</td>
<td>0.921</td>
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<tr>
<td>ITSE</td>
<td>0.422</td>
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<td>0.936</td>
<td>0.906</td>
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<td></td>
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<tr>
<td>OSE</td>
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<td>0.432</td>
<td>0.772</td>
<td>0.763</td>
<td>0.916</td>
<td>0.827</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>PD</td>
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<td>-0.508</td>
<td>-0.191</td>
<td>-0.077</td>
<td>-0.194</td>
<td>-0.254</td>
<td>0.911</td>
<td></td>
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<tr>
<td>PQWL</td>
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<td>0.959</td>
<td>0.622</td>
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<td>0.764</td>
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<td>PU</td>
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<tr>
<td>SATIS</td>
<td>0.748</td>
<td>0.758</td>
<td>0.473</td>
<td>0.375</td>
<td>0.501</td>
<td>0.52</td>
<td>-0.522</td>
<td>0.756</td>
<td>0.689</td>
<td>0.85</td>
</tr>
</tbody>
</table>

*) The diagonal value is the AVE value must be greater than the correlation value between constructs indicated by the AVE value is greater than the correlation between constructs, except for ITSE which is the second order of CSE, ISE, and OSE.