Journal of Information Systems and Informatics
Vol. 7, No. 3, September 2025 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v7i3.1212 Published By DRPM-UBD

# Evaluating Digital Readiness and Teachers' Perceptions of a Digital Based Performance Appraisal System in Secondary Schools

**Heru Karuniawan[1], Lalu Mutawalli[2], Khairul Imtihan[3*]**

[1,2,3]Information System Departement, STMIK Lombok, Praya, Lombok Tengah, Indnonesia
Email: [1]herukaruniyawan@gmail.com, [2]laluallistilo@gmail.com, [3*]khairulimtihan31@gmail.com

**Abstract**

This study investigates the determinants influencing the adoption of digital based performance appraisal systems in secondary schools by integrating the Technology Acceptance Model (TAM) with the Technology Organization Environment (TOE) framework. A quantitative approach was employed, involving 103 teachers from junior and senior secondary schools, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance Performance Map Analysis (IPMA). The results show that perceived ease of use strongly affects both perceived usefulness ($\beta = 0.377$, $p = 0.007$) and behavioral intention ($\beta = 0.678$, $p < 0.001$). Environmental readiness ($\beta = 0.495$, $p < 0.001$) and technological readiness ($\beta = 0.357$, $p < 0.001$) are significant predictors of perceived ease of use, while organizational readiness ($\beta = 0.269$, $p = 0.013$) significantly influences perceived usefulness. Conversely, the direct effect of perceived usefulness on behavioral intention was not significant ($p = 0.142$). The IPMA results emphasize that although environmental and technological readiness exhibit relatively high performance, they still present opportunities for improvement to enhance perceived ease of use. These findings highlight that strengthening usability, infrastructure, and organizational support is crucial for increasing teacher acceptance and ensuring the sustainable implementation of digital based performance appraisal systems in schools.

**Keywords**: technology adoption, TAM, TOE framework, PLS-SEM, IPMA

## 1. INTRODUCTION

The rapid digital transformation in education, driven by global initiatives for sustainable development and technological innovation, has reshaped administrative, learning, and assessment practices worldwide [1], [2]. According to the OECD [3], more than 70% of member countries have adopted digital teacher performance appraisal systems to enhance transparency, accountability, and professional development. In Indonesia, the Ministry of Primary and Secondary Education emphasizes the importance of digital governance in schools [4]. However, most secondary education institutions, particularly in rural and developing regions, continue to rely on manual or semi digital evaluation methods.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

A critical aspect of this transformation is the shift from manual teacher performance appraisal systems to digital based systems designed to enhance accountability, transparency, and efficiency in the evaluation process [5], [6].

Traditional assessment methods that rely on printed forms, spreadsheets, or semi digital tools have proven vulnerable to delays, bias, and inefficiencies, and are incapable of providing the real time feedback essential for teachers' professional development [4], [7]. Although digital performance appraisal systems offer significant potential, their implementation in secondary schools, especially in developing areas, remains limited due to infrastructural constraints, insufficient organizational support, and varying levels of digital competence among educators [8], [9]. Teachers' perceptions of the usefulness and ease of use of such systems are decisive factors in adoption, as explained in the Technology Acceptance Model (TAM) [10], [11], [12]. Conversely, institutional readiness, encompassing technological, organizational, and environmental factors as formulated in the Technology Organization Environment (TOE) framework, strongly influences a school's ability to effectively adopt digital solutions [13], [14]. This issue is particularly relevant for schools that have not yet implemented integrated teacher performance appraisal information systems, where the evaluation process still depends on printed documents or simple digital formats disconnected from school management systems[15]. Consequently, teacher performance evaluations tend to be time-consuming, error-prone, and lacking in transparency. The adoption of digital based performance appraisal systems is expected to improve efficiency, accuracy, and the continuous monitoring of teacher performance [16], [17].

Previous studies in the field of educational technology adoption have yielded varied results, particularly in school contexts with limited technological resources [18]. Some studies highlight the importance of organizational support, training, and infrastructure as key determinants of successful implementation [19], [20], while others emphasize that teachers' perceptions of ease of use and perceived benefits greatly influence their intention to use such systems [12]. Nonetheless, research combining school digital readiness analysis with teachers' perceptions of digital performance appraisal systems in schools without integrated systems remains scarce, especially in the Indonesian context. Reddy et al. [21] developed a digital literacy model to bridge skills gaps, emphasizing the role of user experience and institutional support in technology adoption, though their study did not specifically address secondary education. Kruszyńska-Fischbach et al. [22] examined organizational digital readiness in the healthcare sector and highlighted the importance of managerial support and infrastructure, but their findings remain sector-specific and untested in educational environments. Similarly, Ergado et al. [13] applied the TOE framework in Ethiopian higher education to identify technological and environmental barriers, yet the findings have limited generalizability due to geographical constraints. Antonietti et al. [23] demonstrated

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

that teachers' digital competence significantly influences technology acceptance in vocational education but did not consider organizational readiness factors. Scherer et al. [11], through a meta analysis, confirmed the strength of TAM in explaining teachers' adoption of digital technology; however, the model has yet to be integrated with institutional readiness frameworks such as TOE. To date, empirical evidence integrating TAM and TOE to evaluate the adoption of digital teacher performance appraisal systems in secondary schools, particularly in regions with heterogeneous digital capacity and policy support, remains limited [14], [24].

Given this research gap, the present study aims to evaluate digital readiness and teachers' perceptions regarding the implementation of digital based performance appraisal systems in schools without integrated performance appraisal information systems. Specifically, this study seeks to: (1) identify the level of school digital readiness in terms of technological and organizational aspects; (2) analyze teachers' perceptions of system ease of use and usefulness; (3) examine the relationship between technological and organizational readiness and teachers' perceptions; (4) assess the influence of teachers' perceptions on their intention to use the system; and (5) provide strategic recommendations for stakeholders to design and implement teacher performance appraisal systems aligned with user needs and institutional capacity. This study is expected to contribute theoretically to the development of technology adoption models in the education sector, while offering practical implications for schools and policymakers to accelerate the digitalization of teacher performance appraisal processes.

## 2. METHODS

### 2.1. Research Design

This study employed a quantitative research design with a survey approach to examine teachers' perceptions and organizational readiness toward the adoption of a digital-based teacher performance assessment system at the secondary education level. The study integrates the Technology Acceptance Model (TAM) and the Technology, Organization, Environment (TOE) framework to analyze the relationship between individual perceptions and institutional readiness in influencing adoption intention. The research focuses on junior high schools (SMP), senior high schools (SMA), and vocational high schools (SMK) in Central Lombok Regency, Indonesia, that have not yet implemented a digital based teacher performance assessment system.

### 2.2. Sample and Data Collection

The research population comprised teachers and principals in SMP, SMA, and SMK in Central Lombok Regency. The sampling technique used was purposive

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

sampling with the following inclusion criteria: (1) currently actively teaching in SMP/SMA/SMK in the research area, (2) directly involved in the teacher performance assessment process, and (3) possessing basic digital literacy skills. Data collection was carried out over three months, from June to August 2025, through the distribution of questionnaires both in person (face-to-face) and online to reach urban, semi urban, and rural areas. Of all the questionnaires collected, 103 respondents were deemed valid after data cleaning and completeness checks, and thus all were included in the analysis.

### 2.3. Conceptual Framework, Research Instrument, and Research Hypotheses

This study integrates the Technology Acceptance Model (TAM) and the TOE Framework to evaluate factors influencing teachers' and principals' behavioral intention to adopt a digital teacher performance assessment system[25], [26]. The conceptual model combines external variables from the TOE Framework Environmental Readiness (ER), Organizational Readiness (OR), and Technological Readiness (TR), which influence individual perception variables in TAM, namely Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), which ultimately enhance their intention to use the digital assessment system, Behavioral Intention (BI)[27], [28], [29]. The conceptual framework of this study is illustrated in Figure 1.

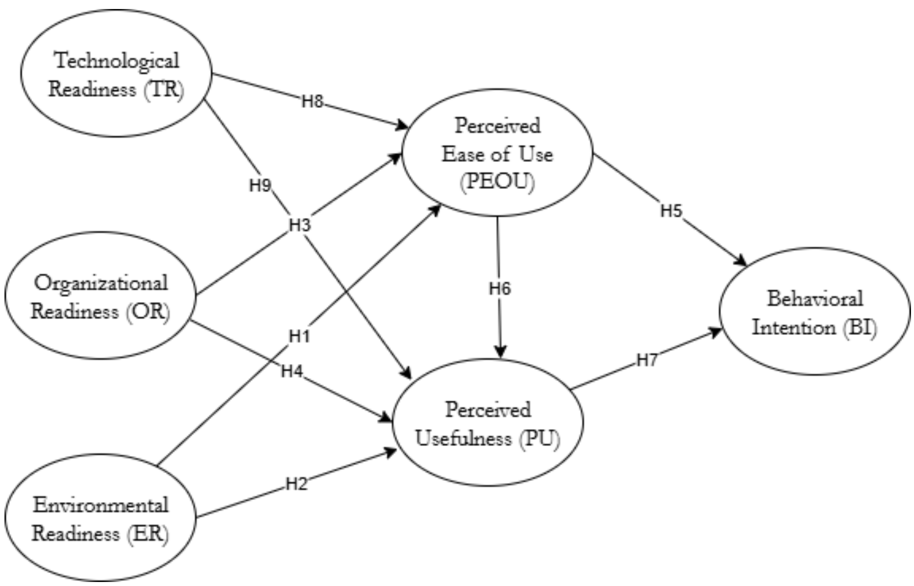


**Figure 1.** Conceptual Framework

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

The research instrument was developed based on validated constructs from previous studies related to technology adoption and organizational readiness, which were then adapted to the educational context. The questionnaire consisted of two parts: (1) respondents' demographic profiles and (2) measurement statements for the research variables. Each construct was measured using three to four reflective indicators on a five point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was reviewed by three academic experts in educational technology and pilot tested on 30 teachers outside the main sample to ensure clarity and reliability. Minor revisions were made based on feedback from the pilot test. Based on the conceptual framework, the research hypotheses are formulated as follows:

H1 : Environmental Readiness has a positive effect on Perceived Ease of Use.
H2 : Environmental Readiness has a positive effect on Perceived Usefulness.
H3 : Organizational Readiness has a positive effect on Perceived Ease of Use.
H4 : Organizational Readiness has a positive effect on Perceived Usefulness.
H5 : Perceived Ease of Use has a positive effect on Behavioral Intention.
H6 : Perceived Ease of Use has a positive effect on Perceived Usefulness.
H7 : Perceived Usefulness has a positive effect on Behavioral Intention.
H8 : Technological Readiness has a positive effect on Perceived Ease of Use.
H9 : Technological Readiness has a positive effect on Perceived Usefulness.

### 2.4. Validity and Reliability Testing

The evaluation of the measurement model followed the criteria recommended by Hair et al. [25], including indicator reliability (outer loading > 0.70), internal consistency reliability (Cronbach's Alpha and Composite Reliability > 0.70), convergent validity (Average Variance Extracted, AVE > 0.50), and discriminant validity tested using the Fornell Larcker criterion and the Heterotrait Monotrait (HTMT) ratio (< 0.85). Indicators that did not meet the statistical thresholds but had theoretical relevance were retained to preserve construct validity [29].

### 2.5. Data Analysis

Data analysis was performed using the Partial Least Squares Structural Equation Modeling (PLS SEM) method with SmartPLS 4.0 software. This method was selected because it is suitable for exploratory research, small to medium sample sizes, and predictive modeling in complex conceptual frameworks such as TAM–TOE integration [30], [31], [32]. The analysis process was conducted in two stages: (1) evaluating the measurement model to ensure construct validity and reliability, and (2) evaluating the structural model to test the research hypotheses. The structural model evaluation included path coefficient analysis, coefficient of determination ($R^2$), effect size ($f^2$), predictive relevance ($Q^2$), and collinearity

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

diagnostics (VIF). Statistical significance testing was performed using a bootstrapping technique with 5,000 resamples. Furthermore, this study also applied Importance Performance Map Analysis (IPMA) to identify constructs with the greatest influence (importance) on the main dependent variable and to assess their performance [33], [34]. IPMA analysis provides practical insights into priority areas that need improvement to maximize the outcomes of implementing the digital based teacher performance assessment system.

## 3. RESULTS AND DISCUSSION

### 3.1. Measurement Model Evaluation

The measurement model was rigorously evaluated to ensure the reliability and validity of the latent constructs prior to structural model analysis. Following the guidelines of Hair et al. [25], [27], the evaluation comprised four key assessments: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

**Tabel 1.** Research Variables, Indicators and Outer Loadings

| Variable | Code | Indicator | Outer Loadings |
|---|---|---|---|
| Technological Readiness | TR1 | The school has adequate hardware (computers/laptops) to support digital operations | 0.906 |
| | TR2 | Internet access at the school is stable and can be used for digital activities | 0.925 |
| | TR3 | Availability of software supporting teacher performance evaluation | 0.935 |
| | TR4 | The school's internal network supports the operation of the digital system | 0.935 |
| Organizational Readiness | OR1 | School leadership encourages the use of digital systems | 0.726 |
| | OR2 | The school provides training for the use of digital systems | 0.754 |
| | OR3 | There is an IT support team or staff within the school | 0.848 |
| | OR4 | The school has internal policies to support digitalization | 0.831 |
| Environmental Readiness | ER1 | Strong support from the education office for school digitalization | 0.880 |
| | ER2 | Existence of national regulations encouraging the adoption of digital systems | 0.860 |
| | ER3 | Availability of assistance/infrastructure from local government | 0.882 |
| Perceived Ease of Use | PEOU 1 | The digital performance appraisal system is easy for teachers to learn | 0.929 |

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

| Variable | Code | Indicator | Outer Loadings |
|---|---|---|---|
| | PEOU 2 | The system interface is easy to understand and use | 0.943 |
| | PEOU 3 | Operating the system does not require much time | 0.907 |
| Perceived Usefulness | PU1 | The system helps accelerate the teacher performance evaluation process | 0.950 |
| | PU2 | The system improves the efficiency of evaluation administration | 0.951 |
| | PU3 | The use of the system enhances the accuracy of evaluation results | 0.859 |
| | PU4 | The system provides useful feedback for teachers | 0.895 |
| Behavioral Intention to Use | BI1 | I intend to use this system if it is implemented | 0.934 |
| | BI2 | I am willing to learn how to use this system | 0.921 |
| | BI3 | I will use this system in evaluation activities | 0.936 |
| | BI4 | I believe this system will be beneficial in the long term | 0.931 |

As presented in Table 1, all outer loadings exceeded the recommended threshold of 0.70, confirming strong associations between the indicators and their respective latent constructs. The loadings ranged from 0.726 (OR1) to 0.951 (PU2), indicating high indicator reliability. Items with slightly lower but acceptable loadings were retained due to strong theoretical justification, in line with Hair et al. [26]. Internal consistency reliability was assessed using Cronbach's alpha (CA), rho_A (ϱA), and composite reliability (CR). As shown in Table 2, all constructs achieved CA values between 0.804 and 0.948, rho_A values between 0.820 and 0.956, and CR values between 0.870 and 0.963, well above the 0.70 threshold, demonstrating satisfactory internal consistency. Convergent validity, evaluated via the Average Variance Extracted (AVE), revealed that all constructs exceeded the minimum recommended value of 0.50, with AVE scores ranging from 0.626 (Organizational Readiness) to 0.865 (Behavioral Intention to Use) (Table 2). These results indicate that over 50% of the variance in the indicators is explained by their respective constructs.

**Table 2.** Construct Reliability and Validity

| Construct | CA | rho_a | rho_c | AVE |
|---|---|---|---|---|
| Behavioral Intention to Use (BI) | 0.948 | 0.950 | 0.963 | 0.865 |
| Environmental Readiness (ER) | 0.846 | 0.846 | 0.907 | 0.764 |
| Organizational Readiness (OR) | 0.804 | 0.820 | 0.870 | 0.626 |
| Perceived Ease of Use (PEOU) | 0.918 | 0.919 | 0.948 | 0.859 |
| Perceived Usefulness (PU) | 0.935 | 0.956 | 0.953 | 0.836 |
| Technological Readiness (TR) | 0.944 | 0.946 | 0.960 | 0.856 |

Note(s): CA : Cronbach's alpha; rho_a : Composite Reliability rho_a; rho_c : Composite Reliability rho_c; AVE :average variance extracted.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Discriminant validity was examined using two approaches: the Heterotrait Monotrait ratio of correlations (HTMT) and the Fornell Larcker criterion. The HTMT results (Table 3) show that all values were below the 0.90 cut off suggested by Henseler et al. [35], [36], confirming that the constructs are empirically distinct. For instance, the HTMT value between Behavioral Intention to Use and Environmental Readiness was 0.745, while the highest observed value between Perceived Ease of Use and Environmental Readiness was 0.893, still below the 0.90 threshold [37].

**Table 3.** Discriminant validity - Heterotrait monotrait (HTMT) ratio

| Construct | BI | ER | OR | PEOU | PU | TR |
|---|---|---|---|---|---|---|
| Behavioral Intention to Use (BI) | | | | | | |
| Environmental Readiness (ER) | 0.745 | | | | | |
| Organizational Readiness (OR) | 0.477 | 0.448 | | | | |
| Perceived Ease of Use (PEOU) | 0.793 | 0.893 | 0.482 | | | |
| Perceived Usefulness (PU) | 0.478 | 0.468 | 0.459 | 0.522 | | |
| Technological Readiness (TR) | 0.732 | 0.786 | 0.395 | 0.797 | 0.363 | |

**Table 4.** Discriminant validity (Fornell Larcker criterion)

| Construct | BI | ER | OR | PEOU | PU | TR |
|---|---|---|---|---|---|---|
| Behavioral Intention to Use (BI) | 0.930 | | | | | |
| Environmental Readiness (ER) | 0.668 | 0.874 | | | | |
| Organizational Readiness (OR) | 0.408 | 0.365 | 0.791 | | | |
| Perceived Ease of Use (PEOU) | 0.741 | 0.787 | 0.416 | 0.927 | | |
| Perceived Usefulness (PU) | 0.462 | 0.420 | 0.428 | 0.492 | 0.914 | |
| Technological Readiness (TR) | 0.693 | 0.703 | 0.341 | 0.743 | 0.346 | 0.925 |

The Fornell Larcker criterion results (Table 4) further validated discriminant validity. The square roots of the AVE values (bolded diagonal entries) for each construct exceeded their corresponding inter construct correlations. For example, the square root of the AVE for Behavioral Intention to Use was 0.930, greater than its highest correlation with any other construct (0.741 with Perceived Ease of Use). This confirms that each construct shares more variance with its own indicators than with those of other constructs.

These findings are visually supported in Figure 2, where all indicator loadings onto their respective constructs are high, and the inter-construct paths align with theoretical expectations. Collectively, the results indicate that the measurement model meets the reliability and validity requirements outlined by Hair et al. [27], enabling progression to structural model evaluation.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

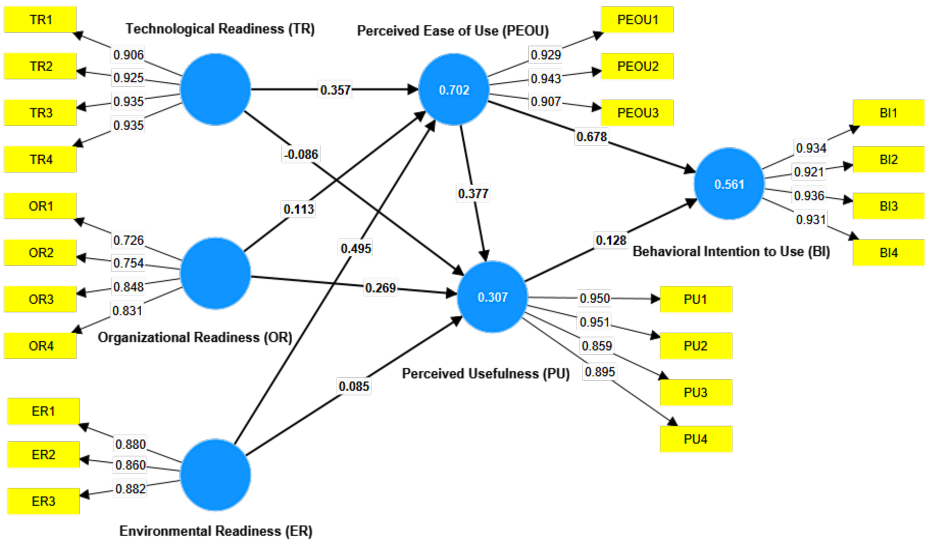


**Figure 2.** Structural model result

### 3.2. Structural Model Assessment

The structural model analysis was conducted to evaluate the causal relationships among latent variables and to test the proposed research hypotheses. This assessment encompassed the interpretation of the coefficient of determination ($R^2$), predictive relevance ($Q^2$), path coefficients, effect sizes ($f^2$), and hypothesis testing results, as presented in Tables 5 and 6. The results in Table 5 indicate that the $R^2$ value for Behavioral Intention to Use (BI) is 0.561, suggesting that 56.1% of the variance in BI can be explained by its predictor variables, namely Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). According to Hair et al. [27], this $R^2$ value falls within the moderate category.

For the PEOU variable, the $R^2$ value of 0.702 demonstrates substantial explanatory power, with 70.2% of its variance accounted for by Environmental Readiness (ER), Organizational Readiness (OR), and Technological Readiness (TR). Furthermore, the $R^2$ value for PU is 0.307, which falls within the low to moderate category, indicating that only 30.7% of its variance can be explained by ER, OR, TR, and PEOU. The $Q^2$ values, obtained through the blindfolding procedure, indicate positive predictive relevance for all endogenous variables. Specifically, BI recorded a $Q^2$ value of 0.469, PEOU achieved 0.583, and PU attained 0.230. All these values are above zero, confirming that the model possesses satisfactory predictive capability for the dependent variables.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

**Table 5.** Structural Model Assessment And Goodness-Of-Fit (Gof)

| Construct | $R^2$ | $R^2$ adjusted | $Q^2$ | T values | P values |
|---|---|---|---|---|---|
| Behavioral Intention to Use (BI) | 0.561 | 0.552 | 0.469 | 4.423 | 0.000 |
| Perceived Ease of Use (PEOU) | 0.702 | 0.693 | 0.583 | 11.499 | 0.000 |
| Perceived Usefulness (PU) | 0.307 | 0.279 | 0.230 | 3.314 | 0.001 |

Note(s): $R^2$ : Coefficient of Determination; $Q^2$: Predictive Relevance.

The hypothesis testing results (Table 6) reveal that, out of the nine proposed hypotheses, five were supported significantly ($p < 0.05$). The strongest path was the relationship between PEOU and BI (H5), with a coefficient $\beta = 0.678$, $t = 8.004$, and an effect size $f^2 = 0.934$, categorized as large. This finding underscores that perceived ease of use is the primary predictor of behavioral intention to use the system. Additionally, ER exerted a significant influence on PEOU (H1: $\beta = 0.495$, $t = 4.912$, $f^2 = 0.441$, large category), while TR had a significant effect on PEOU (H8: $\beta = 0.357$, $t = 3.692$, $f^2 = 0.225$, medium category). OR was also found to significantly influence PU (H4: $\beta = 0.269$, $t = 2.489$, $f^2 = 0.110$, medium category). Furthermore, PEOU significantly affected PU (H6: $\beta = 0.377$, $t = 2.688$, $f^2 = 0.068$, small category).

**Table 6.** Hypothesis Testing Results

| Hypothesis | Relationships | $\beta$ | T-value | P-value | ($f^2$) | VIF | Supported |
|---|---|---|---|---|---|---|---|
| H1 | ER -> PEOU | 0.495 | 4.912 | 0.000 | 0.441 | 2.051 | Yes |
| H2 | ER -> PU | 0.085 | 0.511 | 0.609 | 0.017 | 2.872 | No |
| H3 | OR -> PEOU | 0.113 | 1.727 | 0.084 | 0.048 | 1.173 | No |
| H4 | OR -> PU | 0.269 | 2.489 | 0.013 | 0.110 | 1.216 | Yes |
| H5 | PEOU -> BI | 0.678 | 8.004 | 0.000 | 0.934 | 1.320 | Yes |
| H6 | PEOU -> PU | 0.377 | 2.688 | 0.007 | 0.068 | 3.351 | Yes |
| H7 | PU -> BI | 0.128 | 1.469 | 0.142 | 0.050 | 1.320 | No |
| H8 | TR -> PEOU | 0.357 | 3.692 | 0.000 | 0.225 | 2.011 | Yes |
| H9 | TR -> PU | -0.086 | 0.620 | 0.535 | 0.016 | 2.437 | No |

Note(s): $\beta$= Path Coefficient; $f^2$= Effect Size; VIF: Variance Inflation Factor; ER: Environmental Readiness; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; OR: Organizational Readiness; BI: Behavioral Intention to Use; TR: Technological Readiness.

Conversely, the remaining four hypotheses, H2 (ER → PU), H3 (OR → PEOU), H7 (PU → BI), and H9 (TR → PU), were not supported by the data, as their p-values exceeded 0.05. This suggests that not all readiness variables exert a direct and significant influence on perceived usefulness or behavioral intention. The $f^2$ values indicate the relative contribution of each predictor construct to its dependent variable. Based on Table 6, the path PEOU → BI had the largest contribution ($f^2 = 0.934$), followed by ER → PEOU ($f^2 = 0.441$), TR → PEOU ($f^2 = 0.225$), and OR → PU ($f^2 = 0.110$). Other relationships exhibited small or

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

negligible effects. These findings highlight that perceived ease of use serves as a pivotal mediating factor, channeling the effects of environmental and technological readiness into behavioral intention to use the system

### 3.3. Importance Performance Map Analysis (IPMA)

The IPMA was conducted to identify strategic priorities for enhancing the primary dependent variable, Behavioral Intention to Use (BI), by considering two key dimensions: the level of importance, representing the relative contribution of each construct to the target variable, and the level of performance, reflecting respondents' perceptions of the achievement of each construct. The IPMA results indicate that Environmental Readiness (ER) holds the highest level of importance for Perceived Ease of Use (PEOU) (0.495) with a performance score of 71.279. This finding suggests that environmental readiness, including infrastructure support and external policy, is the dominant factor influencing the perceived ease of system use. Technological Readiness (TR) ranks second with an importance score of 0.357 and a performance of 74.552, highlighting the role of internal technological preparedness in strengthening the perception of ease of use. Meanwhile, Organizational Readiness (OR) shows a lower importance level (0.113) despite its relatively good performance (68.415).

**Table 8.** Importance Performance Map (IPMA)

| Construct | Perceived Ease of Use (PEOU) | | Perceived Usefulness (PU) | | Behavioral Intention to Use (BI) | |
|---|---|---|---|---|---|---|
| | Important | Performance | Important | Performance | Important | Performance |
| ER | 0.495 | 71.279 | 0.271 | 71.279 | 0.370 | 71.279 |
| OR | 0.113 | 68.415 | 0.312 | 68.415 | 0.117 | 68.415 |
| TR | 0.357 | 74.552 | 0.049 | 74.552 | 0.248 | 74.552 |
| PEOU | - | - | 0.377 | 68.067 | 0.726 | 68.067 |
| PU | - | - | - | - | 0.128 | 74.773 |

Note(s): ER: Environmental Readiness; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; OR: Organizational Readiness; BI: Behavioral Intention to Use; TR: Technological Readiness.

For Perceived Usefulness (PU), PEOU exhibits the highest importance score (0.377) with a performance of 68.067, reinforcing the structural model findings that perceived ease of use directly contributes to perceived system usefulness. OR occupies the second position with an importance of 0.312 and performance of 68.415, followed by ER (0.271; performance 71.279). Conversely, TR demonstrates very low importance (0.049) despite high performance (74.552), indicating that it is not a primary focus for PU improvement. Regarding the BI target variable, PEOU stands out as the construct with the highest importance (0.726) and a performance of 68.067, showing that perceived ease of use has a dominant influence on behavioral intention to use the system. ER has moderate importance (0.370) with performance at 71.279, followed by TR (0.248;

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

performance 74.552). PU has a relatively small contribution (0.128) despite its high performance (74.773), suggesting potential for increasing its strategic value through enhancing perceived usefulness. OR ranks last with an importance of 0.117 and performance of 68.415.

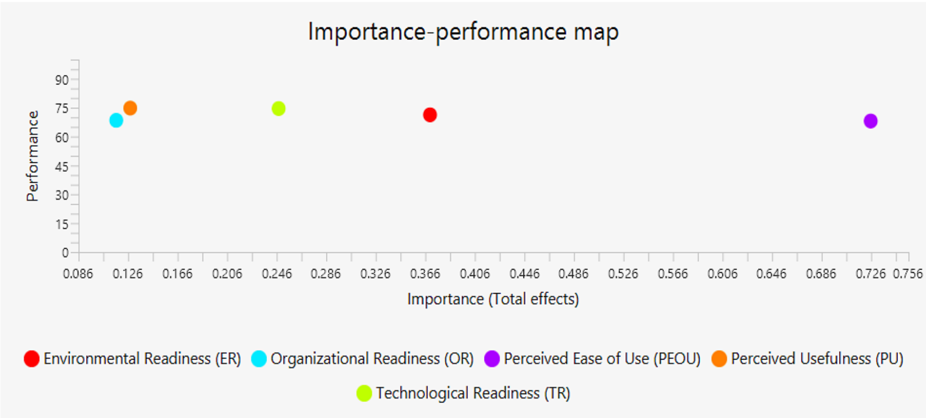


**Figure 3.** Importance Performance Map (IPMA)

Based on the IPMA results, strategic improvement priorities should focus on constructs with high importance but relatively moderate performance. For PEOU, the main focus should be on improving ER and TR, while for PU, optimizing PEOU and strengthening OR are key actions. Regarding BI, enhancing perceived ease of use emerges as the most urgent strategic step, followed by reinforcing environmental readiness. These findings align with previous literature, emphasizing that improvements in ease of use and environmental support significantly strengthen users' intentions to adopt the system.

### 3.4. Discussion

The structural model assessment provides a comprehensive understanding of the relationships among the key constructs in the proposed TAM–TOE integration for evaluating user adoption of the system. The $R^2$ values indicate that the model explains a substantial proportion of variance in the dependent constructs, with Perceived Ease of Use (PEOU) achieving the highest explained variance ($R^2$ = 0.702; adjusted $R^2$ = 0.693), suggesting that the combination of technological, organizational, and environmental readiness strongly predicts users' perception of system ease of use. Behavioral Intention to Use (BI) also demonstrates a substantial $R^2$ value (0.561; adjusted $R^2$ = 0.552), underscoring the model's capacity to capture the determinants of user behavioral intentions. Meanwhile, Perceived Usefulness (PU) records a moderate $R^2$ (0.307; adjusted $R^2$ = 0.279), indicating that while predictors contribute to perceived usefulness, there is still room to integrate

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

additional influencing factors. The predictive relevance values ($Q^2$) for all endogenous constructs PEOU (0.583), BI (0.469), and PU (0.230), are well above zero, confirming that the model possesses substantial predictive accuracy in line with Hair et al. [27].

The path coefficient results from Table 6 provide further insight into the hypothesized relationships. Environmental Readiness (ER) exerts a strong and significant influence on PEOU ($\beta = 0.495$, $p < 0.001$), affirming the critical role of supportive infrastructure, policy environment, and external enablers in shaping perceptions of system ease of use. Similarly, Technological Readiness (TR) significantly impacts PEOU ($\beta = 0.357$, $p < 0.001$), highlighting the importance of internal technological capabilities in facilitating user interaction with the system. Organizational Readiness (OR), while positive, exhibits a smaller yet significant effect on PEOU ($\beta = 0.113$, $p < 0.05$), suggesting that internal organizational support structures contribute but are not the primary driver of perceived ease of use. For PU, PEOU emerges as the most influential predictor ($\beta = 0.377$, $p < 0.001$), consistent with the Technology Acceptance Model's premise that ease of use enhances perceived utility. OR ($\beta = 0.312$, $p < 0.001$) also plays a significant role in shaping PU, implying that organizational structures, resource availability, and managerial support are essential for users to perceive the system as beneficial. ER exerts a moderate effect on PU ($\beta = 0.271$, $p < 0.001$), whereas TR's effect is minimal ($\beta = 0.049$, $p > 0.05$), indicating that technology readiness alone may not substantially enhance the perceived usefulness unless complemented by ease-of-use improvements and organizational support.

Regarding BI, PEOU stands out with the highest path coefficient ($\beta = 0.726$, $p < 0.001$), reinforcing the centrality of usability perceptions in driving adoption intentions. ER ($\beta = 0.370$, $p < 0.001$) and TR ($\beta = 0.248$, $p < 0.001$) follow, indicating that external environment and technology readiness also foster adoption intentions, albeit to a lesser extent. Interestingly, PU's effect on BI is relatively small ($\beta = 0.128$, $p < 0.05$), suggesting that even if users perceive the system as useful, ease of use remains a more decisive factor in determining their willingness to adopt. OR exerts the least influence ($\beta = 0.117$, $p < 0.05$), implying that organizational readiness alone is insufficient to trigger strong behavioral intentions without the mediating effects of PEOU and PU. The effect size ($f^2$) analysis corroborates these findings by identifying PEOU's substantial effect on BI and PU, and ER's large contribution to PEOU. These results collectively emphasize that interventions targeting ease of use and environmental support will yield the greatest improvement in adoption metrics.

The Importance Performance Map Analysis (IPMA) in Table 7 offers practical insights by linking statistical significance with performance priorities. For PEOU, ER holds the highest importance (0.495) with a performance score of 71.279,

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

marking it as a key area for strategic focus. TR ranks second in importance (0.357; performance = 74.552), followed by OR (0.113; performance = 68.415). For PU, PEOU dominates in importance (0.377) with performance at 68.067, confirming its role as the principal driver of perceived usefulness. OR (0.312) and ER (0.271) follow, while TR's low importance (0.049) despite high performance (74.552) suggests that further investment in TR may yield diminishing returns for PU enhancement. When targeting BI, PEOU again emerges as the most critical driver (importance = 0.726; performance = 68.067), demonstrating that user-centric design and system usability should remain the primary development priorities. ER (importance = 0.370) and TR (importance = 0.248) are secondary drivers, while PU's modest importance (0.128) despite high performance (74.773) indicates untapped potential to amplify its strategic value. OR ranks lowest in importance (0.117; performance = 68.415), reaffirming its limited direct influence on adoption intentions.

Integrating the structural model and IPMA findings, the discussion underscores that strategic efforts should prioritize enhancing system ease of use through improvements in environmental and technological readiness, while sustaining high usability standards to reinforce both perceived usefulness and adoption intentions. These results align with prior TAM and TOE studies [38], [39], which highlight usability and external support as critical enablers of technology adoption. In practical terms, stakeholders should focus on reinforcing external infrastructure and policy alignment, investing in intuitive system interfaces, and providing adequate organizational support to maximize both perceived ease of use and user behavioral intentions.

The findings of this study provide several strategic insights for policymakers and public sector managers seeking to optimize the adoption of technology-based information systems. First, the strong influence of *Perceived Ease of Use* (PEOU) on *Behavioral Intention* (BI) highlights the critical importance of designing intuitive, responsive, and user-friendly interfaces. Public organizations should allocate sufficient resources to enhance user experience through streamlined and functional system designs, comprehensive training programs, and clear usage documentation. Such efforts not only improve perceived ease of use but also directly foster long-term technology adoption.

Second, the Importance-Performance Map Analysis (IPMA) results indicate that Environmental Readiness (ER) holds high importance yet demonstrates relatively moderate performance. This suggests that external factors such as supportive regulations, policies, and infrastructure are essential prerequisites for successful system implementation. Local governments and related agencies should ensure the availability of enabling policies, stable connectivity, and a conducive technological ecosystem to minimize adoption barriers. Alignment between macro-level policies

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

and technical readiness will strengthen users' positive perceptions of the system. Third, the significant impact of Technological Readiness (TR) on PEOU underscores the need for continuous investment in internal technological infrastructure. Regular hardware and software upgrades, server capacity enhancements, and the implementation of advanced data security protocols are essential to ensure optimal system performance. Considering TR's relatively high performance in the IPMA, improvement efforts can be directed toward innovative aspects such as cloud-based integration and artificial intelligence applications for personalized services.

Fourth, while Organizational Readiness (OR) shows a comparatively lower direct effect, it remains a critical factor that should be strengthened through workforce capacity building, business process restructuring, and fostering a technology-adaptive organizational culture. Visionary leadership and effective internal communication will accelerate adoption processes and reduce resistance to change. The managerial implications emphasize that technology adoption strategies in the public sector should be holistic, integrating interventions across technical, organizational, and environmental dimensions. Managers should adopt a data-driven approach, leveraging IPMA results to prioritize areas with the greatest potential impact on behavioral intention while ensuring the sustainability of training programs and technical support. This comprehensive approach will not only ensure technical success but also deliver tangible benefits to both users and organizations in the long term.

## 4. CONCLUSION

This study investigated the factors influencing the adoption of a technology-based information system in the public sector by integrating the Technology Acceptance Model (TAM) with the Technology Organization Environment (TOE) framework. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance Performance Map Analysis (IPMA), the research examined the relationships among environmental readiness, technological readiness, organizational readiness, perceived ease of use, perceived usefulness, and behavioral intention to use. The structural model results confirmed that perceived ease of use plays a pivotal role in shaping both perceived usefulness and behavioral intention, thereby validating its central position in technology adoption models. Environmental readiness emerged as a critical driver of perceived ease of use, while technological readiness also demonstrated a substantial influence, underscoring the importance of both external support and internal technological infrastructure. Organizational readiness contributed positively to perceived usefulness, indicating the relevance of institutional capacity and cultural preparedness in reinforcing perceived system value. The IPMA results provided additional strategic insights by highlighting that environmental readiness and technological readiness, despite their

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

relatively high performance, still offer substantial opportunities for improvement to maximize perceived ease of use. Similarly, organizational readiness requires targeted enhancement to strengthen perceived usefulness, while perceived ease of use itself should remain a primary focus to improve behavioral intention to use. The findings emphasize that a holistic approach, integrating environmental, technological, and organizational interventions is essential for optimizing system adoption in the public sector. By prioritizing the improvement of high-importance yet moderate performance factors, policymakers and managers can design more effective strategies to enhance user acceptance and ensure the long-term sustainability of technology implementation

## REFERENCES

[1] UNESCO, "The United Nations World Water Development Report 2023: partnerships and cooperation for water; executive summary - UNESCO Digital Library," Paris, France: UNESCO, 2023. Accessed: Aug. 14, 2025. [Online]. Available: https://unesdoc.unesco.org/ark:/48223/pf0000384657

[2] N. Khan, A. Sarwar, T. B. Chen, and S. Khan, "Connecting digital literacy in higher education to the 21st century workforce.," *Knowledge Management & E-Learning*, vol. 14, no. 1, pp. 46–61, 2022.

[3] OECD, "Digital Education Outlook 2024: Shaping Teacher Performance Evaluation," Paris, France: OECD Publishing. Accessed: Aug. 14, 2025. [Online]. Available: https://www.oecd.org/en/publications/education-policy-outlook-2024_dd5140e4-en.html

[4] Z. Ullah *et al.*, "Achieving organizational social sustainability through electronic performance appraisal systems: The moderating influence of transformational leadership," *Sustainability*, vol. 13, no. 10, p. 5611, 2021.

[5] K. F. Ferine, R. Murliasari, A. Saefudin, and F. Fahruddin, "From manual to digital: an innovation in the performance appraisal system of Medan city government employees," *Asian Journal of Management, Entrepreneurship and Social Science*, vol. 4, no. 02, pp. 1208–1225, 2024.

[6] Z. Zhen, Z. Yousaf, M. Radulescu, and M. Yasir, "Nexus of digital organizational culture, capabilities, organizational readiness, and innovation: Investigation of SMEs operating in the digital economy," *Sustainability*, vol. 13, no. 2, p. 720, 2021.

[7] D. K. Nguyen, T. Broekhuizen, J. Q. Dong, and P. C. Verhoef, "Digital readiness: construct development and empirical validation," 2019.

[8] C. Betsurmath, H. K. Mamatha, S. B. Chidambaram, and V. Prashant, "Design, Development and validation of a digital performance based appraisal system: a planned approach in change management," *Indian J Sci Technol*, vol. 17, no. 6, pp. 548–555, 2024.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[9] Y.-Y. Yap, S.-H. Tan, and S.-W. Choon, "Elderly's intention to use technologies: a systematic literature review," *Heliyon*, vol. 8, no. 1, 2022.
[10] K. Imtihan and M. R. Mardi, "The Impact of Visual Quality and User Interface Responsiveness on Student Satisfaction in Academic Information Systems (AIS)," *Pakistan Journal of Life and Social Sciences (PJLSS)*, vol. 22, no. 2, 2024, doi: 10.57239/PJLSS-2024-22.2.001455.
[11] R. Scherer, F. Siddiq, and J. Tondeur, "The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education," *Comput Educ*, vol. 128, pp. 13–35, 2019.
[12] C. Troise, A. O'Driscoll, M. Tani, and A. Prisco, "Online food delivery services and behavioural intention–a test of an integrated TAM and TPB framework," *British food journal*, vol. 123, no. 2, pp. 664–683, 2021.
[13] A. A. Ergado, A. Desta, and H. Mehta, "Determining the barriers contributing to ICT implementation by using technology-organization-environment framework in Ethiopian higher educational institutions," *Educ Inf Technol (Dordr)*, vol. 26, pp. 3115–3133, 2021.
[14] D. Setiawan, J. Marzal, and L. E. Fitri, "Integrating religiosity with Technology Acceptance Model (TAM) and Technology Organization Environment (TOE) frameworks: A study on ICT adoption in micro and small enterprises," *Pakistan Journal of Commerce and Social Sciences (PJCSS)*, vol. 18, no. 3, pp. 651–675, 2024.
[15] S. M. S. Alam, "Unveiling the Effects of ICT Adoption in the Apparel Sector of Bangladesh Based on Technology-Organization-Environment Framework," *Asia Pacific J Inf Syst*, vol. 33, no. 4, pp. 977–998, 2023.
[16] A. Aman, K. Imtihan, and M. Rodi, "Evaluating User Satisfaction and Public Engagement in Local Government Social Media," *International Journal of Engineering, Science and Information Technology*, vol. 5, no. 3, pp. 235–248, Jun. 2025, doi: 10.52088/ijesty.v5i3.905.
[17] M. Amini and N. Jahanbakhsh Javid, "A multi-perspective framework established on diffusion of innovation (DOI) theory and technology, organization and environment (TOE) framework toward supply chain management system based on cloud computing technology for small and medium enterprises," *Organization and Environment (TOE) Framework Toward Supply Chain Management System Based on Cloud Computing Technology for Small and Medium Enterprises (January 2023). International Journal of Information Technology and Innovation Adoption*, vol. 11, pp. 1217–1234, 2023.
[18] A. V. Martín-García, F. Martínez-Abad, and D. Reyes-González, "TAM and stages of adoption of blended learning in higher education by application of data mining techniques," *British Journal of Educational Technology*, vol. 50, no. 5, pp. 2484–2500, 2019, doi: 10.1111/bjet.12831.
[19] K. Imtihan, M. Mardi, A. Tantoni, W. Bagye, and M. Zulkarnaen, "Enhancing User Satisfaction and Loyalty in MSMEs: The Role of

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Accounting Information Systems," *Journal of Information Systems and Informatics*, vol. 7, no. 1, Mar. 2025, doi: 10.51519/journalisi.v7i1.1044.

[20] O. A. Alismaiel, J. Cifuentes-Faura, and W. M. Al-Rahmi, "Social media technologies used for education: An empirical study on TAM model during the COVID-19 pandemic," in *Frontiers in Education*, Frontiers Media SA, 2022, p. 882831.

[21] P. Reddy, K. Chaudhary, and S. Hussein, "A digital literacy model to narrow the digital literacy skills gap," *Heliyon*, vol. 9, no. 4, 2023.

[22] A. Kruszyńska-Fischbach, S. Sysko-Romańczuk, T. M. Napiórkowski, A. Napiórkowska, and D. Kozakiewicz, "Organizational e-health readiness: How to prepare the primary healthcare providers' services for digital transformation," *Int J Environ Res Public Health*, vol. 19, no. 7, p. 3973, 2022.

[23] C. Antonietti, A. Cattaneo, and F. Amenduni, "Can teachers' digital competence influence technology acceptance in vocational education?," *Comput Human Behav*, vol. 132, p. 107266, 2022.

[24] A. M. Al-Rahmi *et al.*, "The influence of information system success and technology acceptance model on social media factors in education," *Sustainability*, vol. 13, no. 14, p. 7770, 2021.

[25] J. Hair and A. Alamer, "Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example," *Research Methods in Applied Linguistics*, vol. 1, no. 3, p. 100027, 2022, doi: 10.1016/j.rmal.2022.100027.

[26] J. F. Hair Jr *et al.*, "An introduction to structural equation modeling," *Partial least squares structural equation modeling (PLS-SEM) using R: a workbook*, pp. 1–29, 2021, doi: 10.1007/978-3-030-80519-7_1.

[27] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," Jan. 14, 2019, *Emerald Group Publishing Ltd.* doi: 10.1108/EBR-11-2018-0203.

[28] J. F. Hair, C. M. Ringle, S. P. Gudergan, A. Fischer, C. Nitzl, and C. Menictas, "Partial least squares structural equation modeling-based discrete choice modeling: an illustration in modeling retailer choice," *Business Research*, vol. 12, no. 1, pp. 115–142, 2019.

[29] M. Sarstedt, J. F. Hair, M. Pick, B. D. Liengaard, L. Radomir, and C. M. Ringle, "Progress in partial least squares structural equation modeling use in marketing research in the last decade," *Psychol Mark*, vol. 39, no. 5, pp. 1035–1064, 2022, doi: 10.1002/mar.21640.

[30] H. M. Alzoubi, "Factors affecting ChatGPT use in education employing TAM: A Jordanian universities' perspective," *International Journal of Data and Network Science*, vol. 8, no. 3, pp. 1599–1606, 2024.

[31] M. Al-Emran, I. Arpaci, and S. A. Salloum, "An empirical examination of continuous intention to use m-learning: An integrated model," *Educ Inf Technol (Dordr)*, vol. 25, no. 4, pp. 2899–2918, 2020, doi: 10.1007/s10639-019-10094-2.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[32] M. Alshurideh, B. Al Kurdi, and S. A. Salloum, "Examining the main mobile learning system drivers' effects: A mix empirical examination of both the Expectation-Confirmation Model (ECM) and the Technology Acceptance Model (TAM)," in *International conference on advanced intelligent systems and informatics*, Springer, 2019, pp. 406–417.

[33] F. Setiawan and F. Antonio, "Human resources strategy improving perceived performance outcome infection control in hospital: importance-performance map analysis," *International Journal of Environment, Workplace and Employment*, vol. 7, no. 4, pp. 319–339, 2023.

[34] C. Tam, D. Santos, and T. Oliveira, "Exploring the influential factors of continuance intention to use mobile Apps: Extending the expectation confirmation model," *Information Systems Frontiers*, vol. 22, pp. 243–257, 2020.

[35] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J Acad Mark Sci*, vol. 43, no. 1, pp. 115–135, Jan. 2015, doi: 10.1007/s11747-014-0403-8.

[36] M. Sarstedt, N. F. Richter, S. Hauff, and C. M. Ringle, "Combined importance–performance map analysis (cIPMA) in partial least squares structural equation modeling (PLS–SEM): a SmartPLS 4 tutorial," *Journal of Marketing Analytics*, pp. 1–15, 2024, doi: 10.1057/s41270-024-00325-y.

[37] G. F. Khan, M. Sarstedt, W.-L. Shiau, J. F. Hair, C. M. Ringle, and M. P. Fritze, "Methodological research on partial least squares structural equation modeling (PLS-SEM) An analysis based on social network approaches," *Internet Research*, vol. 29, no. 3, pp. 407–429, 2019, doi: 10.1108/IntR-12-2017-0509.

[38] N. Venkatesvara Rao, D. Venkatavara Prasad, and M. Sugumaran, "Real-time video object detection and classification using hybrid texture feature extraction," *International Journal of Computers and Applications*, vol. 43, no. 2, pp. 119–126, 2021.

[39] K. K. de S. Oliveira and R. A. C. De Souza, "Digital transformation towards education 4.0," *Informatics in Education*, vol. 21, no. 2, pp. 283–309, 2022.