International Journal of Cyber and IT Service Management (IJCITSM)
Vol. 4, No. 2, October 2024, pp. 122−132
E-ISSN: 2808-554X | P-ISSN: 2655-8807, DOI:10.34306

The Impact of Information Technology Support on the Use of E-Learning Systems at University

Aan Kanivia[1], Hilda[2], Alfri Adiwijaya[3], Muhammad Faizal Fazri[4*], Sabda Maulana[5], Marviola Hardini[6]

[1]Department of Accounting, Catur Insan Cendekia University, Indonesia
[2]Department of Accounting, Bank Negara Indonesia, Indonesia
[3]Department of Digital Business, REY Incorporation, Indonesia
[4]Department of Technology Information, University of Raharja, Indonesia
[5]Department of Digital Business, Alfabet Inkubator Indonesia, Indonesia
[6]Department of Technology Information, Association of Indonesian Private Universities, Indonesia
[1]aankanivia@cic.ac.id, [2]hilda@raharja.info, [3]alfri.adiwijaya@raharja.info, [4]faizal.fazri@raharja.info, [5]sabda@raharja.info, [6]marviola@raharja.info
***Corresponding Author**

Article Info

Article history:

Submission July 30, 2024
Revised August 18, 2024
Accepted September 27, 2024
Published October 14, 2024

Keywords:

ITS
E-Learning
University
Education
Learning System

ABSTRACT

E-learning technologies at educational institutions like University of Raharja are essential in enabling flexible and accessible education in this period of significant digital revolution. **This study** examines how Information Technology Support (ITS) affects user satisfaction, perceived usefulness, perceived ease of use, and intention to reuse concerning e-learning systems efficacy. Unlike prior Technology Acceptance Model (TAM) based studies, **this research** emphasizes the specific role of ITS dimensions, such as infrastructure and technical training, in non Western educational contexts. This provides unique insights for improving e-learning systems in higher education. This study assesses the reactions of 500 users of University of Raharja e-learning system using Structural Equation Modeling (SEM) with the PLS technique. Results indicate that perceived ease of use and perceived usefulness are greatly increased by strong ITS, which in turn has a beneficial effect on User Satisfaction and Intention to Reuse. **This study** aligns with the Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education) by enhancing the accessibility and quality of education through e-learning systems, SDG 9 (Industry, Innovation, and Infrastructure) by emphasizing the importance of robust IT infrastructure and technical training, and SDG 10 (Reduced Inequalities) by addressing the digital divide in non Western educational settings. Additionally, ITSs SDG 17 (Partnerships for the Goals) **by encouraging** collaboration between educational institutions, technology providers, and policymakers to optimize e-learning outcomes. According to the study findings, ITS must be strengthened to maximize e-learning system performance, raise user happiness, and promote continuous usage.

DOI: https://doi.org/10.34306/ijcitsm.v4i2.166

1. INTRODUCTION

In today digital era, e-learning has become an essential component in higher education, enabling universities to expand the scope and quality of their education [1]. University of Raharja has adopted e-learning technology as an integral part of education, providing flexible and inclusive access for students to learn without being bound by geographical or time constraints [2]. The use of e-learning technology not only allows adaptation to various student learning styles but also supports more collaborative and interactive education through digital tools. However, the success of an e-learning system depends not only on the course content provided but also on effective ITS. ITS includes a strong infrastructure, a reliable learning management system, and adequate technical support services, which together create a conducive and responsive learning environment [3].

The implementation of e-learning aligns with several Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), which emphasizes ensuring inclusive and equitable quality education and promoting lifelong learning opportunities for all [4]. E-learning provides students with access to quality education regardless of geographical limitations, fostering inclusivity. Additionally, the focus on robust IT infrastructure and support aligns with SDG 9 (Industry, Innovation, and Infrastructure) by promoting technological innovation in education. Furthermore, by addressing barriers faced by diverse learners, especially in non Western contexts, this study contributes to SDG 10 (Reduced Inequalities), aiming to bridge the gap in educational opportunities for students from different socio-economic backgrounds [5].

Although e-learning offers many benefits, its implementation at University of Raharja faces several challenges [6]. Unlike prior studies that predominantly explore ITS in Western contexts, this study uniquely examines its influence in an Indonesian university setting, where cultural, infrastructural, and administrative factors differ significantly. Comparative analysis of ITS dynamics in this setting adds originality to the existing body of literature, particularly in higher education [7]. One of them is the variation in acceptance and use of the system by lecturers and students. Factors such as technology reliability, ease of use, and available technical support often influence adoption rates and user satisfaction. Additionally, inconsistencies in ITS can cause frustration and hinder the learning experience, potentially reducing the effectiveness of e-learning programs [8]. Considering the importance of these factors, this research aims to evaluate in depth how ITS influences the use of e-learning systems at University of Raharja. This research will use theoretical models such as the TAM to better understand how Perceived Ease of Use (PEU) and Perceived Usefulness (PU) are influenced by the quality of ITS [9]. By understanding these aspects, universities can develop more effective strategies to improve IT infrastructure and support services, thereby maximizing the benefits of e-learning investments [10].

This research will also examine how variations in ITS can influence individuals perceptions of e-learning technology and how this influences their satisfaction and intention to reuse the system. By understanding this relationship, University of Raharja hopes to implement more effective strategies to increase the acceptance and effectiveness of e-learning systems, thereby improving the quality of the learning process and user satisfaction [11]. These efforts also contribute to SDG 17 (Partnerships for the Goals) by fostering collaborations between educational institutions, technology providers, and policymakers to create sustainable solutions in higher education. Thus, this research is not only important for academic development but also strategic in the broader context of educational administration [12].

2. LITERATURE REVIEW

Recent studies have underlined the significance of ITS in advancing e-learning adoption in developing regions [13]. For instance, the critical role of targeted ITS strategies in mitigating digital divides across Southeast Asia [14]. Similarly, IT infrastructure and user training as primary drivers for improving e-learning acceptance in Indonesian higher education institutions. These findings align with the objectives of this research and provide a broader contextual relevance for the study focus [15].

Perceived Ease of Use (PEU) refers to the degree to which users believe that using the system will be free of effort, while Perceived Usefulness (PU) denotes the extent to which users feel the system enhances their performance. These constructs, fundamental to the TAM, provide a framework for understanding user adoption behavior [16]. The term ”Information Technology” (IT) support is frequently used in the literature on technology-based education to refer to the Technology Acceptance Model created by [17]. According to TAM, users adoption of technology is mostly influenced by perceived utility and perceived ease of use [18]. Within the realm of e-learning, competent IT assistance may enhance these two perspectives by offering dependable infrastructure and prompt technical help, hence promoting user adoption and use of e-learning platforms [19]. Moreover, evaluating the efficacy of e-learning systems can benefit from the use of DeLone and McLean information system success model. According to this model, user happiness and system utilization may be significantly predicted by factors such as system quality, information quality, and service quality. In the context of e-learning, IT assistance can reinforce these three factors [20].

Various studies have examined The impact of ITS on enhancing e-learning outcomes. For example, research found that technical quality, including technical reliability and support, contributes significantly to user satisfaction with e-learning systems [21]. Another study shows that an efficient IT infrastructure plays an important role in facilitating access and navigation of e-learning systems, which directly affects the user learning experience [22]. Research on the other hand, identified that in some cases, despite adequate IT infrastructure, a lack of technical support and effective training for end users leads to suboptimal utilization of e-learning systems [23]. This underlines the importance of a holistic approach that focuses not only on technical aspects but also on user support.

Although much research has identified critical components of ITS that influence e-learning use, there remains a paucity in the literature regarding how these elements interact specifically in the context of higher education in developing countries [24]. Additionally, previous research tends to focus on measuring user satisfaction without exploring the specific influence of each ITS dimension on satisfaction and continued use. Therefore, this research aims to fill this gap by evaluating the specific impact of various aspects of ITS on the effectiveness of the e-learning system at University of Raharja, providing new insights on how to increase the application of e-learning technology in the academic environment [25].

3. RESEARCH METHODOLOGY

The SEM-PLS approach was selected due to its robustness in analyzing complex models with latent variables, particularly in exploratory research contexts [26]. Unlike covariance based SEM, which is typically used for confirmatory analysis and requires large sample sizes, SEM-PLS focuses on maximizing explained variance (R^2). This makes it highly suitable for this study, which aims to explore the multidimensional relationships between ITS, perceived ease of use, perceived usefulness, user satisfaction, and intention to reuse within a relatively small dataset. Additionally, SEM-PLS accommodates non normal data distributions, which further validates its use in this context. The present study employed the SEM method with the PLS approach to investigate the impact of ITS on the use of e-learning systems at University of Raharja [27]. SEM-PLS is particularly suited for this study due to its ability to analyze complex relationships between latent variables while accommodating non normal data distributions and relatively small sample sizes. Unlike covariance based SEM, PLS focuses on maximizing explained variance and is effective for exploratory studies like this. The PEU, PU, and three sub variables of ITS, IT Infrastructure, Technical Support, and IT Training are among the variables that are based on the TAM. Additionally, we assess the end consequences of e-learning by measuring Intention to Reuse (IR) and User Satisfaction (US) [28].

Data for this study will be gathered via surveys that 500 instructors and students at University of Raharja who utilize the e-learning system completed. Every variable will be measured using a Likert scale in the survey questions [29]. Following data collection, path coefficients, t values, and R squared were used in the data analysis process using PLS-SEM software to assess the construct validity and reliability [30]. In order to verify the importance and dependability of study findings in relation to the hypothesis put forward, construct validity is examined utilizing Convergent Validity, Discriminant Validity, and Reliability techniques, such as Average Variance Extracted (AVE) and Cronbach Alpha.

As summarized in Figure 1, this research hypothesis was designed to test the key elements of ITS and how these elements influence the e-learning user experience, from perceptions of ease and usefulness to satisfaction and continued intention in its use [31].

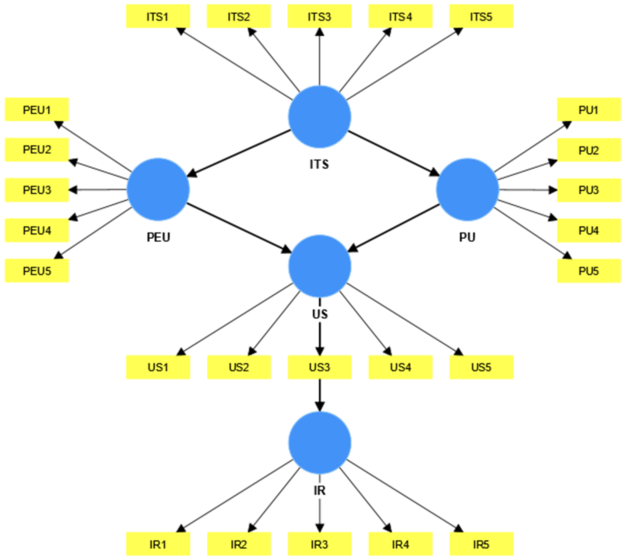

Figure 1. Hypothesized Relationships Among ITS Variables and E-Learning Adoption Metrics.

As shown in Figure 1, the model hypothesizes that ITS directly influences both PEU and PU, which in turn affect US and IR. This framework underscores the interconnected pathways critical for optimizing e-learning system adoption [32]. In this research, five hypotheses have been designed to test the influence of ITS and user perceptions of the e-learning system at University of Raharja. The following is an explanation for each hypothesis:

- H1: Relationship between ITS and PEU.

  The purpose of this hypothesis is to investigate how much university IT infrastructure and support services affect how user-friendly e-learning platforms are. It is anticipated that robust ITS would reduce technical issues and improve system accessibility, making the system simpler to use.

- H2: Relationship between ITS and PU.

  This hypothesis investigates whether users perceptions of the e-learning system usability are influenced by the university effectiveness in providing IT assistance. Perceived usefulness refers to the degree to which users believe the e-learning platform enhances their performance in the workplace or the classroom. It is predicted that a system with strong ITS will be more beneficial due to its superior and more dependable features and functioning.

- H3: Connection between PEU and US.

  This hypothesis looks at how user happiness is affected by how simple users believe e-learning systems to be. Users are likely to be happier with their overall learning experience if they find an e-learning system straightforward to use. Simple navigation and an intuitive user interface are frequently linked to ease of use.

- H4: Relationship between PU and US.

  This hypothesis focuses on the relationship between how useful an e-learning system is perceived by users and their level of satisfaction with the system. The perception that e-learning systems provide real benefits in an educational context can increase user satisfaction because they feel added value in using the technology.

- H5: Relationship between US and IR.

  This final hypothesis evaluates how satisfaction with an e-learning system influences users intentions to continue using the system in the future. High satisfaction typically contributes to greater levels of loyalty and continued intent to interact with the system, reflecting the successful adoption of e-learning technology.

Each of these hypotheses aims to reveal various aspects of the influence of IT on the e-learning experience, from technical aspects to subjective user perceptions, all of which are important in optimizing the implementation and use of e-learning systems in academic environments [33].

4. RESULTS AND DISCUSSION

The reliability and validity of the constructs in this study demonstrate extremely excellent data quality, according to the analytical findings shown in Table 1. All of the constructions Cronbach Alpha and Composite Reliability (rhoa and rhoc) values are above the 0.7 cutoff, which typically. These results, which fell between 0.750 to 0.902, show that participant replies had a high degree of internal consistency. Furthermore, the majority of the variance in the indicators may be explained by the constructs they measure, according to the Average Variance Extracted (AVE) measure for each construct, which evaluates convergent validit. With the exception of PU, which was exactly at the 0.503 criterion, all constructs had AVE values over 0.5, suggesting that more testing or the addition of items may be required to improve the construct convergent validity.

Table 1. Reliability and Validity of the Constructs Used in the SEM-PLS Model.

	Cronbach alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
IR	0.858	0.872	0.897	0.636
ITS	0.864	0.867	0.902	0.648
PEU	0.855	0.858	0.896	0.634
PU	0.750	0.782	0.832	0.503
US	0.849	0.854	0.892	0.624

Table 1 presents the reliability and validity results of the constructs. All Cronbach alpha and composite reliability values exceed the threshold of 0.7, confirming internal consistency. The AVE values indicate sufficient convergent validity for all variables except PU, which may require further refinement in future studies.

Based on Table 1 findings, the research data is considered reliable and valid for carrying out further analysis of the relationship between variables using SmartPLS This further study will look at the connections between US, PU, IR, and PEU concerning ITS. The statistical significance of these correlations will be ascertained by the path analysis findings, which will offer compelling evidence in favor of or against the hypothesis. Therefore, the findings of this study will be extremely helpful in formulating plans to improve University of Raharja e-learning system implementation and user satisfaction. All of the dependent variables in this study had high values, as can be seen from the R-square and Adjusted R-square data shown in Table 2, suggesting that the tested model has extremely excellent predictive capacity. The US variable, in particular, has the highest Adjusted R-square value of 0.925 and R-square value of 0.926, respectively. This demonstrates that the model independent variables account for almost 92.6% of the variance in user happiness, offering compelling proof that ITS significantly affects users satisfaction with e-learning platforms. This lends credence to hypotheses H3 and H4, which contend that sufficient IT assistance and training boost user happiness and encourage system reuse.

Table 2. R-square and R-square Adjusted Results

	R-square	**R-square Adjusted**
IR	0.777	0.774
PEU	0.590	0.585
PU	0.870	0.868
US	0.926	0.925

Based on Table 2 PU has extremely high R-square (0.870) and Adjusted R-square (0.868) values, meaning that the independent factors examined in this study account for about 87% of the variance in perceived usefulness. This high number suggests that, as suggested by H2, strong IT infrastructure and training have a significant impact on how users view the usability of e-learning systems. Additionally, the independent variable accounts for approximately 59% of the variance in perceived ease of use, as seen by the R-square values of 0.590 and 0.585 for PEU. As per H1, although being lower than PU and US, this figure indicates a substantial correlation between ITS and the e-learning system ease of use. Lastly, the R-square value of 0.777 and the Adjusted R-square of 0.774 for the IR variable show that about 77.7% of the variance in users intention to reuse the e-learning system can be explained by the independent variable. Positive experiences with the system considerably improve the chance of continuing usage, which is consistent with H4, which relates user pleasure with continuous intention to use the system.

Overall, the results of the R-square and Adjusted R-square analyses provide strong validation for the model used and support the hypotheses proposed in this study. These results underscore the importance of effective ITS in increasing acceptance and satisfaction with e-learning systems. Bootstrapping is a resampling method used to obtain an estimate of the sample distribution from a statistical estimator by repeating sampling with the replacement of the original data. In this research, it can be seen in Figure 2 that bootstrapping plays a crucial role in obtaining more precise estimates regarding the reliability of parameters and for testing statistical hypotheses regarding the estimated effects between variables.

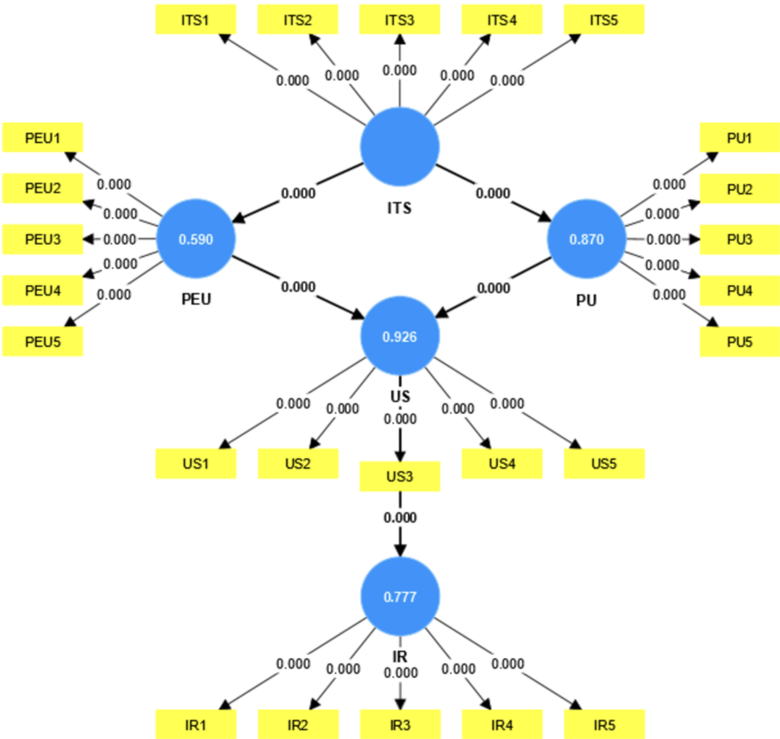

Figure 2. Bootstrapping Results

Figure 2 The bar chart above illustrates the significant improvements in latency, efficiency, and cost reduction that come with integrating edge computing into IoT systems. These advancements demonstrate the practical benefits of edge computing but also highlight the importance of addressing associated challenges, such as hardware limitations and regulatory compliance, to realize its full potential across industries. By overcoming these obstacles, businesses can leverage edge computing to create more flexible, scalable, and efficient IoT ecosystems. In the bootstrapping process, a large number of 5.000 samples are drawn randomly from the original data with replacement to estimate the sample distribution of the estimator. From each of these samples, the path coefficient, t-statistic, and p-value can be calculated. The degree of correlation between the independent and dependent variables is shown by the path coefficient. P-values act as border values between findings that are statistically significant and those that are not, and t-statistics are used to assess if the path coefficient is statistically significant. Values greater than or equal to 0.05 indicate values that are not statistically significant. Meanwhile, a value smaller than 0.05 indicates a statistically significant value. By using the bootstrapping technique in this research, we can be more confident about the strength and significance of the relationship found between ITS and the TAM variables measured, namely Perceived Ease of Use, Perceived Usefulness, User Satisfaction, and Intention to Reuse. This strengthens the conclusions drawn from the data and provides a more solid basis for recommendations resulting from the research.

The findings of evaluating path coefficients in the context of Structural Equation Modeling SEM with PLS for this study are shown in Table 3 utilizing the bootstrap approach.

Table 3. Path Coefficients

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (O/STDEV)**	**P values**
ITS → PEU	0.706	0.766	0.060	12.701	0.000
ITS → PU	0.933	0.937	0.012	75.409	0.000
PEU → US	0.841	0.838	0.040	21.107	0.000
PU → US	0.166	0.171	0.045	3.692	0.000
US → IR	0.881	0.889	0.022	40.477	0.000

From the results in Table 3 we can draw several important conclusions regarding the relationships between variables in the research model.

- H1: Relationship between ITS and PEU.

  A highly strong and statistically significant association (P value = 0.000) is demonstrated by the path coefficient from ITS to PEU, which is 0.706 with a T-statistics value of 12.701. This provides credence to the idea that users perceptions of the usability of e-learning platforms are enhanced when institutions provide better assistance for information technology. The high coefficient value suggests that a robust IT infrastructure has a significant impact on system usability.

- H2: The association between ITS and PU.

  The e-learning system is very strong and consistent, as evidenced by the very high path coefficient of 0.933, T-statistics of 75.409, and a P value around zero (0.000). This demonstrates that it is a significant element influencing users perceptions of the usefulness of an e-learning system.

- H3: Connection between US and PEU.

  With T-statistics of 21.107 and a P value of 0.000, the path coefficient from PEU to US is 0.841, suggesting a very significant and robust association. These findings provide credence to the theory that user happiness is significantly influenced by the perceived ease of use of the e-learning system; the more user-friendly the system, the more satisfied users are.

- H4: Connection between US and PU.

  The path coefficient of 0.166 with T-statistics of 3.692 and a P value of 0.000 indicates a strong positive association between PU and US, although being lower than other correlations. This suggests that although perceived usefulness has a lesser effect on user happiness than PEU, it nevertheless adds to it.

- H5: US and IR are related.

  The extremely significant correlation between user satisfaction and their desire to use the e-learning system again is confirmed by the very high coefficient of 0.881, T-statistics of 40.477, and P value of 0.000. This implies that consumers are more likely to stick with an e-learning system in the future if they are happier with it.

In conclusion, the results of path coefficients analysis using the bootstrap technique show that all the relationships hypothesized in this model are significant and provide strong support for the proposed theoretical model. This confirms the importance of effective ITS in improving the e-learning experience at University of Raharja and shows that user satisfaction plays an important role in determining the intention to continue using the system.

4.1. Impact on IoT Systems

The integration of edge computing into IoT systems has significantly improved the scalability and real-time processing capabilities of IoT deployments. The ability to process data closer to the source has allowed IoT systems to scale by supporting an increasing number of connected devices without overloading centralized cloud systems. This has led to more flexible and responsive networks that can handle larger volumes of data without compromising speed or accuracy. In the context of smart cities, edge computing enables more efficient use of urban infrastructure. For example, IoT sensors for traffic lights and roads can instantly adjust traffic flow without communicating with remote cloud servers, reducing both congestion and energy consumption. Similarly, advanced artificial intelligence allows cameras and sensors to analyze video feeds in realtime, helping to detect accidents or security breaches immediately.

For industrial IoT, the combination of edge computing and predictive analytics has improved operational efficiency by enabling real-time monitoring and rapid response to potential equipment failures. This real-time monitoring reduces downtime and maintenance costs and allows systems to flexibly adapt to changing conditions without waiting for cloud-based analytics.

4.2. Challenges in Implementation

While edge computing has clearly improved the performance of IoT systems, its implementation poses a number of challenges that must be addressed to achieve wider adoption. One of the main issues is the hardware limitations of the devices. Unlike centralized cloud systems that have virtually unlimited computing power and storage, many edge devices are resource constrained. These devices often need to perform advanced analytics or run AI models locally, but their limited computing resources can make this difficult, especially for complex applications that require significant processing power.

Scalability is another important concern. Managing a large, distributed network of edge devices introduces coordination and maintenance complexity. Coordinating updates, ensuring consistent performance, and troubleshooting across hundreds, if not thousands, of edge devices, is much more complex than managing a centralized system. Organizations need advanced management tools and platforms to effectively monitor, update, and control the entire network.

Additionally, regulatory compliance is a challenge for industries that handle sensitive data, such as healthcare and finance. Processing data at the edge, especially in environments with privacy regulations such as General Data Protection Regulation (GDPR) or Health Insurance Portability and Accountability Act (HIPAA), requires stringent security protocols to ensure data protection. This includes the need for encryption and authentication mechanisms at the edge and during data transfer between devices and the cloud. Ensuring compliance across distributed networks of edge devices can be resource intensive and requires robust security frameworks.

5. MANAGERIAL IMPLICATION

Based on the findings, it is crucial for university management to prioritize investment in high-quality ITS. This includes enhancing both the technical infrastructure and technical support services that directly influence the usability and perceived benefits of e-learning systems. Managers should focus on ensuring a reliable IT infrastructure that supports seamless access to the system and quick resolution of technical issues, as this significantly impacts user satisfaction and the likelihood of system reuse.

Further, improving user satisfaction through ITS will positively affect the perception of e-learning systems, fostering higher user engagement and retention. Therefore, university administrators should allocate resources to continuously upgrade ITS services and infrastructure, ensuring that they meet the evolving needs of users. By doing so, they can improve both the operational efficiency of e-learning systems and the long-term success of e-learning initiatives at the university. This strategy will also increase the likelihood that students and faculty will continue to use the system, contributing to the overall success of digital learning environments at the institution.

6. CONCLUSION

The analysis findings consistently demonstrate that perceived usability and ease of use of e-learning systems are significantly influenced by ITS, particularly when it comes to technical support and IT infrastructure. This, in turn, affects user satisfaction and the likelihood that they will use the system again. The results of the study indicate that there is a significant positive correlation between the quality of ITS and PU and PEU. This correlation is strong and has high path coefficients, suggesting that improving the quality of ITS can lead to improvements in system performance. Users feel the benefits and convenience of e-learning.

In particular, the relationship between ITS and PU with a path coefficient of 0.933 and a very high T-statistics value (75.409) stands out as the most dominant influence in this model. This shows that users perceive real benefits from the e-learning system supported by a strong IT infrastructure and efficient technical support services, which in turn greatly increases the perceived usability of the system. These findings underscore the importance of developing and maintaining a reliable IT infrastructure and responsive technical support as key factors in increasing user acceptance of e-learning technologies.

The conclusion that can be drawn from this research is that investment in ITS not only increases the operational efficiency of e-learning systems but also increases positive perceptions and user satisfaction, which is crucial for the long-term success of e-learning implementation. High user satisfaction is closely related to the intention to reuse the system, as shown by the strong relationship between US and IR. Therefore, University of Raharja is advised to continue to improve its ITS and focus on developing robust infrastructure and effective support services to maximize user satisfaction and retention of the title learning system.

7. SUGGESTION

Drawing from the findings of a study conducted at University of Raharja on the influence of IT assistance on e-learning system usage, some recommendations may be made to enhance present procedures and guide future investigations. First, In addition to improving IT infrastructure, it is crucial for administrators to design user-centric training programs tailored for both lecturers and students. This includes workshops on e-learning system navigation, troubleshooting technical issues, and adapting teaching strategies for digital platforms. These efforts should prioritize inclusivity and cultural adaptability, ensuring the ITS strategies meet the needs of diverse stakeholders in non-Western contexts. This will enhance how user-friendly and useful the e-learning system is judged to be. Second, it is crucial to provide thorough training curricula that address both the integration of e-learning platforms into the classroom and their technical usage for instructors and students. To further understand the elements impacting the efficacy of e-learning, Future research could focus on comparative analyses across universities in Indonesia to understand regional variations in ITS needs. Additionally, exploring emerging factors such as artificial intelligence integration and mobile learning adaptability would enrich the current understanding of e-learning system effectiveness.

8. DECLARATIONS

8.1. About Authors

Aan Kanivia (AK) -

Hilda (HH) -

Alfri Adiwijaya (AA) -

Muhammad Faizal Fazri (MF) -

Sabda Maulana (SM) https://orcid.org/0000-0002-0871-6463

Marviola Hardini (MH) https://orcid.org/0000-0003-3336-2131

8.2. Author Contributions

Conceptualization: AK; Methodology: HH; Software: MF; Validation: SM and MH; Formal Analysis: HH and AA; Investigation: SM; Resources: MH; Data Curation: AK; Writing Original Draft Preparation: AK and AA; Writing Review and Editing: AK and MH; Visualization: sm; All authors, AK, HH, AA, MF, SM, MM have read and agreed to the published version of the manuscript.

8.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.4. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] A. Szymkowiak, B. Melović, M. Dabić, K. Jeganathan, and G. S. Kundi, "Information technology and gen z: The role of teachers, the internet, and technology in the education of young people," *Technology in Society*, vol. 65, p. 101565, 2021.

[2] A. G. Prawiyogi, M. Hammet, and A. Williams, "Visualization guides in the understanding of theoretical material in lectures," *International Journal of Cyber and IT Service Management*, vol. 3, no. 1, pp. 54–60, 2023.

[3] F. Ouyang, L. Zheng, and P. Jiao, "Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020," *Education and Information Technologies*, vol. 27, no. 6, pp. 7893–7925, 2022.

[4] S. Z. Mirsharapovna, S. M. Shadjalilovna, A. A. Kakhramonovich, and K. R. Malikovna, "Pros and cons of computer technologies in education," *Texas Journal of Multidisciplinary Studies*, vol. 14, pp. 26–29, 2022.

[5] Y. El Archi and B. Benbba, "The applications of technology acceptance models in tourism and hospitality research: A systematic literature review," *Journal of Environmental Management & Tourism*, vol. 14, no. 2, pp. 379–391, 2023.

[6] M. Murtaza, Y. Ahmed, J. A. Shamsi, F. Sherwani, and M. Usman, "Ai-based personalized e-learning systems: Issues, challenges, and solutions," *IEEE access*, vol. 10, pp. 81 323–81 342, 2022.

[7] M. R. Anwar and L. D. Sakti, "Integrating artificial intelligence and environmental science for sustainable urban planning," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 179–191, 2024.

[8] A. Ruangkanjanases, A. Khan, O. Sivarak, U. Rahardja, and S.-C. Chen, "Modeling the consumers' flow experience in e-commerce: The integration of ecm and tam with the antecedents of flow experience," *SAGE Open*, vol. 14, no. 2, p. 21582440241258595, 2024.

[9] A. P. Febrina, H. R. Ngemba, S. Hendra, Y. Anshori, and A. Azizah, "Serli discovery learning dalam mendukung pembelajaran ilmu pengetahuan alam siswa berbasis android: Serli discovery learning in supporting android-based natural science learning for students," *Technomedia Journal*, vol. 9, no. 1, pp. 130–142, 2024.

[10] O. Chernikova, N. Heitzmann, M. Stadler, D. Holzberger, T. Seidel, and F. Fischer, "Simulation-based learning in higher education: A meta-analysis," *Review of educational research*, vol. 90, no. 4, pp. 499–541, 2020.

[11] K. Brundiers, M. Barth, G. Cebrián, M. Cohen, L. Diaz, S. Doucette-Remington, W. Dripps, G. Habron, N. Harré, M. Jarchow *et al.*, "Key competencies in sustainability in higher education—toward an agreed-upon reference framework," *Sustainability Science*, vol. 16, pp. 13–29, 2021.

[12] M. Yusuf, M. Yusup, R. D. Pramudya, A. Y. Fauzi, and A. Rizky, "Enhancing user login efficiency via single sign-on integration in internal quality assurance system (espmi)," *International Transactions on Artificial Intelligence*, vol. 2, no. 2, pp. 164–172, 2024.

[13] S. Criollo-C, A. Guerrero-Arias, Á. Jaramillo-Alcázar, and S. Luján-Mora, "Mobile learning technologies for education: Benefits and pending issues," *Applied Sciences*, vol. 11, no. 9, p. 4111, 2021.

[14] R. Heriyanto and T. Mariyanti, "Poverty alleviation strategies through sharia microfinance institutions politico-economics study with tawhidi approach," *Aptisi Transactions on Management*, vol. 6, no. 2, pp. 132–141, 2022.

[15] R. Bhandari and M. V. A. Sin, "Optimizing digital marketing in hospitality industries," *Startupreneur Bisnis Digital (SABDA Journal)*, vol. 2, no. 1, 2023.
[16] S. Choi, Y. Jang, and H. Kim, "Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools," *International Journal of Human–Computer Interaction*, vol. 39, no. 4, pp. 910–922, 2023.
[17] A. S. Al-Adwan, N. Li, A. Al-Adwan, G. A. Abbasi, N. A. Albelbisi, and A. Habibi, "Extending the technology acceptance model (tam) to predict university students' intentions to use metaverse-based learning platforms," *Education and Information Technologies*, vol. 28, no. 11, pp. 15 381–15 413, 2023.
[18] H. Abuhassna, W. M. Al-Rahmi, N. Yahya, M. A. Z. M. Zakaria, A. B. M. Kosnin, and M. Darwish, "Development of a new model on utilizing online learning platforms to improve students' academic achievements and satisfaction," *International Journal of Educational Technology in Higher Education*, vol. 17, pp. 1–23, 2020.
[19] A. Fernanda, M. Huda, and A. R. F. Geovanni, "Application of learning cloud computing technology (cloud computing) to students in higher education," *International Journal of Cyber and IT Service Management*, vol. 3, no. 1, pp. 32–39, 2023.
[20] M. Jahiri, I. I. D. Yusuf *et al.*, "Penerapan e-learning sebagai media pembelajaran berbasis aplikasi android menggunakan metode research and development," *Technomedia Journal*, vol. 8, no. 2 Special Issues, pp. 261–275, 2023.
[21] A. Shater, A. AlMahdawi, and M. Khasawneh, "The digital learning of disabled students: Perceptions of teachers in public schools," *Inf. Sci. Letters. Int. J*, vol. 12, pp. 879–887, 2023.
[22] B. Gros and F. J. García-Peñalvo, "Future trends in the design strategies and technological affordances of e-learning," in *Learning, design, and technology: An international compendium of theory, research, practice, and policy*. Springer, 2023, pp. 345–367.
[23] A. Argani and W. Taraka, "Pemanfaatan teknologi blockchain untuk mengoptimalkan keamanan sertifikat pada perguruan tinggi," *ADI Bisnis Digit. Interdisiplin J*, vol. 1, no. 1, pp. 10–21, 2020.
[24] C. Udeozor, F. Russo-Abegão, and J. Glassey, "Perceptions and factors affecting the adoption of digital games for engineering education: a mixed-method research," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 2, 2023.
[25] N. C. Burbules, G. Fan, and P. Repp, "Five trends of education and technology in a sustainable future," *Geography and sustainability*, vol. 1, no. 2, pp. 93–97, 2020.
[26] E. Smith, N. A. Santoso, N. Azizah, E. D. Astuti *et al.*, "Exploration of the impact of social media on children's learning mechanisms," *CORISINTA*, vol. 1, no. 1, pp. 33–40, 2024.
[27] G. S. Putra, I. I. Maulana, A. D. Chayo, M. I. Haekal, R. Syaharani *et al.*, "Pengukuran efektivitas platform e-learning dalam pembelajaran teknik informatika di era digital," *Jurnal MENTARI: Manajemen, Pendidikan dan Teknologi Informasi*, vol. 3, no. 1, pp. 19–29, 2024.
[28] X. Li, H. Xu, J. Zhang, and H.-h. Chang, "Deep reinforcement learning for adaptive learning systems," *Journal of Educational and Behavioral Statistics*, vol. 48, no. 2, pp. 220–243, 2023.
[29] E. Raisah, S. Rahagi *et al.*, "Enhancing digital payment adoption: The impact of digital literacy on e-wallet usage intention," in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2024, pp. 1–6.
[30] A. Almufarreh and M. Arshad, "Promising emerging technologies for teaching and learning: Recent developments and future challenges," *Sustainability*, vol. 15, no. 8, p. 6917, 2023.
[31] N. Siregar, F. Firmansyah, and Y. S. Harahap, "Developing students' worksheet for english language teaching to cope with the 4c's skill through project based learning," *Jurnal Paedagogy*, vol. 10, no. 1, pp. 44–52, 2023.
[32] D. Y. Park and H. Kim, "Determinants of intentions to use digital mental healthcare content among university students, faculty, and staff: motivation, perceived usefulness, perceived ease of use, and parasocial interaction with ai chatbot," *Sustainability*, vol. 15, no. 1, p. 872, 2023.
[33] M. Karnati, A. Seal, D. Bhattacharjee, A. Yazidi, and O. Krejcar, "Understanding deep learning techniques for recognition of human emotions using facial expressions: A comprehensive survey," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–31, 2023.