

Exploring Students' Acceptance in Using Immersive Virtual Reality (IVR) and Metaverse Integrated Learning Environment

Nuryusmawati Mohd Yusof¹, *Faizah Mashahadi¹, Janiffa Saidon¹, Faizah Sohidi¹, Syed Asherene Syed Omar¹,
Mohd Fikri Ishak¹, Syed Mustaqim Syed Yusof²

¹Faculty of Business Management, University Teknologi Mara, Selangor, Malaysia

²IX Telecom, BIT Group Sdn Bhd, Cyberjaya, Selangor, Malaysia

Email: nuryusmawati@uitm.edu.my, *faizahmashahadi@uitm.edu.my, janiffa@uitm.edu.my,
faiza746@uitm.edu.my, asherene@uitm.edu.my, fikriishak@uitm.edu.my, syedmustaqim@gmail.com

Corresponding Author: Faizah Mashahadi

Abstract: The combination of immersive technologies such as Virtual Reality (VR) and the Metaverse is changing the educational patterns by offering interactive, personalized, engaging learning experiences. This research studied the student acceptance in immersive VR and Metaverse-based learning environments through the Technology Acceptance Model (TAM) model. This research examined the influence of perceived usefulness, perceived ease of use, and attitude on behavioral intention among university students in University Teknologi MARA (UiTM) Puncak Alam. By using a quantitative research design, data were collected from 103 undergraduate students via a structured questionnaire. Through regression analysis, it was revealed that only perceived ease of use and attitude significantly influenced students' behavioral intentions to adopt virtual reality in their learning activities, but not perceived usefulness. These findings highlighted the importance of a friendly user interface and positive emotional engagement in the adoption of virtual reality. The results also contributed to the ongoing discussion on education technology acceptance and provided some insights for software designers, educators, and policymakers for designing and implementing the virtual environment online effectively. Some suggestions for future research were also suggested to explore more variables, such as trust, self-efficacy, and institutional support to further enhance the understanding of adoption behavior across diverse educational methods.

Keywords: *Immersive Virtual Reality, Metaverse, Learning, Education, Technology Acceptance Model*

1. Introduction and Background

The modern education is undergoing a transformative shift, driven significantly by the integration of immersive technologies, particularly Virtual Reality (VR) and the Metaverse. The history of virtual reality in education started in the 1960s, with the experimental simulators such as Morton Heilig's Sensorama that is used for training and entertainment (Jerald, 2015). Nevertheless, virtual reality is being used in formal educational settings only materialized in the early 1990s, driven by the advancement in computer graphics and head-mounted display designs (Pantelidis, 1993). Virtual reality has transitioned from a promising, experimental tool to an accessible and commercial learning tool through the ever-changing technology. This scenario enables learners to engage with sophisticated three-dimensional, interactive environments and simulations, nurturing deeper learning across diverse disciplines, including medicine, engineering, and language acquisition (Radianti et al., 2020).

Virtual Reality is defined as a fully immersive, computer-generated environment that facilitates realistic and embodied user interaction with digital objects and spaces (Milgram & Kishino, 1994). Metaverse is defined as an extension of Virtual Reality, a persistent, shared, and social three-dimensional digital space that effortlessly integrates digital and physical realities. In this expanded definition, users are allowed to engage in learning, collaboration, and creative activities within a comprehensive virtual universe (Mystakidis, 2022). The purpose of the Metaverse in education is to cultivate highly interactive and collaborative learning experiences that surpass the conventional limitations of traditional classrooms, thus promoting learning environments that are more flexible, inclusive, and globally interconnected (Freina & Ott, 2015).

As technologies continue their rapid advancement and integration into educational standards, one critical question emerges: understanding the student acceptance and adoption behaviors of virtual reality in the learning process. The Technology Acceptance (TAM) Model was first developed by Davis (1989), offers a robust theoretical framework for systematically exploring technology adoption. This model originally suggests that an individual's behavioral intention to use a novel technology is primarily influenced by their perceived usefulness

(the conviction that the technology will enhance task performance) and their perceived ease of use (the belief that utilizing the technology will be effortless). In this study TAM Model serves as an important analytical tool for assessing student behavioral intentions in using newer learning technology. This model focuses more narrowly on individual cognitive evaluation, which aligns well with the context of voluntary students' use of immersive Virtual Reality and Metaverse platforms in higher education.

The characteristic of immersive qualities of Virtual Reality, added with the extensive connectivity offered by the Metaverse, present unparalleled opportunities for cultivating active, participatory, and highly personalized learning experiences (Radianti et al., 2020). Nevertheless, despite the significant promise held by these innovations, important questions persist regarding the students' perceptions, acceptance levels, and their behavioral intentions to adopt such technologies within the setting of formal educational contexts. By applying the established TAM Model, this study aims to systematically investigate the important factors that drive students' acceptance and intention to utilize immersive virtual reality and metaverse-integrated learning environments. The findings from this study will also contribute valuable insights into the transformative role of immersive technologies like Virtual Reality in shaping the future of education. Further, these findings may also contribute to some recommendations for instructional designers, educational institutions, and policymakers in the intricate and evolving landscape of digital learning.

2. Literature Review

The Technology Acceptance Model (TAM) is one of the important foundational frameworks in understanding users' acceptance and use of technology. Originating from Davis (1989), the model theorizes that perceived usefulness (PU), perceived ease of use (PEOU), and attitude toward use (ATU) significantly influence an individual's behavioral intention (BI) to adopt newer technology. Recent developments and empirical research conducted between 2022 and 2025 have further validated and expanded the TAM Model across various industries, technologies, and demographic groups. This literature review highlighted key findings from recent studies and journal articles, emphasizing the dynamic roles of perceived usefulness (PU), perceived ease of use (PEOU), and attitude toward use (AT) on behavioral intention (BI).

Previous research revealed that perceived usefulness and perceived ease of use positively influenced students' perceptions and intentions to use mobile payments, which is a newer technology in payment methods (Bahaj, 2025). This study also confirms the robustness of the TAM model in the adoption of newer technology among younger demographics, illustrating that cost considerations plus other factors as explained previously are becoming more prominent in shaping behavioral intentions. Wargadinata (2025) extended TAM Models to the context of rural AI healthcare applications. The study highlighted that organizational capability and user self-efficacy significantly enhanced acceptance of AI-based technologies at the village level. The better the infrastructure and organizational support, the higher the users' self-confidence and subsequent intention to adopt the technology (Wargadinata, 2025). These studies are some of the important studies that highlighted the robustness of the TAM framework that can be used in many different scenarios.

Shen et al. (2024) have conducted a study that confirmed the significance of perceived usefulness and ease of use in shaping users' willingness to adopt virtual reality technologies in education. Further study by Shen et al. (2024) in different industry settings found that perceived usefulness also appeared as the more influential determinant, indicating that users prioritize functional benefits over simplicity when dealing with complex and high-risk technologies. This concept is also agreed by a study from Rosli and Saleh (2024), wherein they found perceived usefulness, personal innovativeness, and perceived enjoyment significantly influenced students' behavioral intentions in acceptance of virtual reality and metaverse in educational applications. Nevertheless, perceived ease of use did not have a significant direct impact on behavioral intention, suggesting that in immersive technologies, users may accept usability challenges if the perceived benefits and enjoyment are high (Rosli & Saleh, 2024).

In García et al. (2024) study, they have found that perceived ease of use remained the key driver for continuous learning engagement. Their findings in this study reinforced the classic TAM Model assumption that ease of access and interaction support sustained technology use in educational settings are important in accepting and adopting newer technology. Wibowo et al. (2024) applied TAM Model to analyze digital business intentions among students and found that perceived usefulness (PU) and perceived ease of use (PEOU) have a high

influence on adopting digital business platforms. This study further reinforces TAM's versatility across various domains, especially in the post-pandemic digital economy, where online entrepreneurship is on the rise.

Musyaffi et al. (2024) also emphasized factors influencing adoption, like perceived usefulness and performance expectancy were crucial, aligning with earlier findings by Martin et al. (2022). Their research underlined the importance of perceived performance benefits in driving adoption among small businesses with limited resources. Alzahrani (2023) also analyzed the TAM Model through the perspective of university educators using technologies in educational institutions and found that both perceived usefulness (PU) and perceived ease of use (PEOU) significantly influenced the intention, mediated by self-efficacy. This study has shown an alignment with TAM Model extensions by incorporating other factors such as motivational and capability, to better explain technology acceptance among professional users.

Choung et al. (2022) and Nagy & Hajdu (2022) both examined the role of trust in artificial intelligence systems, found that trust indirectly affected behavioral intention through perceived usefulness (PU) and attitude (AT). Nagy & Hajdu (2021) identified trust as a stronger predictor than perceived ease of use (PEOU) in artificial intelligence-based online shopping systems. Further, these studies highlighted the importance of trust as one of many external variables in accepting artificial intelligence, suggesting a need to further extend the TAM Model to include psychological and emotional constructs.

3. Research Methodology

This study used a quantitative, descriptive research design aimed at investigating the influence of perceived usefulness (PU), perceived ease of use (PEOU), and attitude (AT) on behavioral intention (BI) in adopting newer specific learning technology among university students. The TAM Model served as the theoretical foundation, providing a structured framework to evaluate the relationships between the constructs.

The target population for this study consisted of students from the Faculty of Business and Management at Universiti Teknologi MARA (UiTM) Puncak Alam Campus. A non-probability convenience sampling method was adopted to distribute the survey to students who were accessible and willing to participate. A total of 103 responses were collected. This sample size exceeded the commonly recommended threshold for regression analysis, which is typically set at 10 to 15 observations per predictor variable (Hair et al., 2019), and is therefore considered sufficient for reliable analysis and generalization within the study context.

Data were collected using a self-administered structured questionnaire, adapted from established instruments from the TAM Model (e.g., Davis, 1989; Venkatesh & Davis, 2000). The questionnaire comprised four main constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATT), and Behavioral Intention to Use (BI). Each construct was measured using 4–5 items on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire was pilot-tested to ensure clarity and reliability of the items. The survey was distributed electronically via university networks and social media platforms. Students were invited to participate voluntarily, without coercion or prejudice. All participants were assured of anonymity and confidentiality, and informed that their responses would be used solely for academic purposes.

The data were analyzed using SPSS software. Descriptive statistics were used to summarize demographic information and general trends in responses. Reliability analysis was conducted using Cronbach's alpha to assess the internal consistency of the constructs. A value of $\alpha \geq 0.70$ was considered acceptable, indicating good internal reliability (Nunnally & Bernstein, 1994). For hypothesis testing, multiple linear regression analysis was performed to observe the influence of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (AT), on Behavioral Intention to Use (BI). The level of statistical significance was set at $p < 0.05$, following standard inferential guidelines (Cohen, 1988; Pallant, 2020).

This study was conducted in accordance with ethical research standards. Before participation, students were presented with a brief overview of the study and a consent form embedded in the survey. Participation was voluntary and students could withdraw at any point. The survey did not include any prejudiced, discriminatory, or sensitive questions, ensuring a fair and respectful research process.

4. Results

This section presents sets of results relating to the profile of respondents with regard to demographic and geographic characteristics (gender, age, level of education, and region).

Profile of Respondents: Table 1 presents the demographic characteristics of the sample. The sample comprised mostly female respondents ($n = 96$, 92.3%), with a smaller proportion of males ($n = 8$, 7.7%). All participants were within the 18–24 age range ($n = 104$, 100%), and all were pursuing an undergraduate (diploma/bachelor's) level of education ($n = 104$, 100%). In terms of household income, the majority earned below RM50,000 per year ($n=80$, 76.9%), followed by RM150,001–RM200,000 ($n = 16$, 15.4%) and RM50,001–RM100,000 ($n = 8$, 7.7%). Regarding prior experience with Virtual Reality (VR), 69.2% of participants ($n = 72$) indicated that they had used VR before, whereas 30.8% ($n = 32$) had not. The frequency of using Virtual Reality (VR) for learning varied among respondents, with 53.8% ($n = 56$) reporting that they had never used Virtual Reality (VR), 30.8% ($n = 32$) had used it occasionally and 15.4% ($n = 16$) rarely used it at all.

Table 1: Demographic and Geographic Information of Students

Variables	Category	Frequency (n)	Percentage (%)
Gender	Female	96	92.3
Gender	Male	8	7.7
Age	18–24	104	100.0
Education Level	Undergraduate (Diploma/Bachelor's)	104	100.0
Household Income (Annually)	Below RM50,000	80	76.9
Household Income (Annually)	RM150,001–RM200,000	16	15.4
Household Income (Annually)	RM50,001–RM100,000	8	7.7
Have you ever used Virtual Reality (VR)?	Yes	72	69.2
Have you ever used Virtual Reality (VR)?	No	32	30.8
Frequency of VR Usage for Learning	Never	56	53.8
Frequency of VR Usage for Learning	Occasionally	32	30.8
Frequency of VR Usage for Learning	Rarely	16	15.4

Descriptive Statistics: The descriptive statistics for the key constructs, presented in Table 2, indicate that students generally responded positively to the immersive VR and metaverse learning environment. For perceived usefulness (PU), this construct had a mean of 4.19 ($SD = 0.68$), suggesting that students found the technology highly beneficial for supporting their learning. This finding is consistent with prior research (Davis, 1989; Radianti et al., 2020). Meanwhile, attitude towards use (AT) also registered a mean of 4.21 ($SD = 0.68$), indicating that most participants in general have favorable perceptions towards using immersive virtual reality for learning. This aligns with the TAM Model (Davis, 1989) and studies by Mystakidis (2022). Further, perceived ease of use (PEU) received a mean score of 3.92 ($SD = 0.71$), suggesting that participants felt reasonably comfortable navigating the virtual platforms. This result is comparable to prior research (Radianti et al., 2020). Lastly, behavioral intention to use (BI) yielded a mean of 4.00 ($SD = 0.71$), indicating that students expressed strong intentions to adopt and continue using the immersive learning platforms. This finding was consistent with other empirical studies done by Venkatesh et al. (2003).

The relatively low standard deviation figures across all constructs (0.68–0.71) further imply a moderate consensus in perceptions and behavioral intention within the sample. These findings supported the theoretical tenets of the TAM Model and highlighted the potential of virtual reality as an effective and well-received tool for modern education and learning.

Table 2: Descriptive Statistics

Variables	Factor Name	Mean	Std. Dev. (SD)
PU	Perceived Usefulness	4.192	0.6804
PEU	Perceived Ease of Use	3.917	0.7060
AT	Attitude Towards Use	4.205	0.6769
BH	Behavioral Intention	3.995	0.7071

Regression Analysis: Regression Analysis is a statistical method used to examine and quantify the relationships between one or more independent variables (predictors) and a dependent variable (outcome). It helps researchers understand the extent and direction to which certain factors influence an outcome. For instance, in technology acceptance studies, it can determine how perceptions like usefulness, ease of use, and attitudes predict learners' behavioral intentions (Field, 2013). Regression is a cornerstone of statistical modeling due to its ability to assess the strength and significance of relationships, and to estimate and predict outcomes from observed data (Tabachnick & Fidell, 2019).

The results (see Table 3) indicated that the overall model was highly significant and accounted for a substantial proportion of the variance in behavioral intention to use (BI). The three constructs altogether explained approximately 81.2% of the variance ($R^2 = .812$, Adjusted $R^2 = .806$) in the outcome variable, suggesting that the combined effects of attitude, perceived usefulness, and perceived ease of use, these three constructs had a strong and meaningful influence on students' behavioral intentions. With a standard error of the estimate of 0.242, the model demonstrated satisfactory predictive accuracy.

Table 3: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.901 ^a	.812	.806	.24156

a. Predictors: (Constant), Attitude, Perceived Usefulness, Perceived Ease of Use

The results of the multiple regression analysis (see Table 4) revealed that perceived ease of use (PEU) was the strongest and significant determinant of behavioral intention (BI) ($B = 0.744$, $\beta = .717$, $t = 8.22$, $p < .001$). This suggested that respondents who found easy easy-to-operate virtual reality (VR) learning environment were more likely to adopt and utilize it. This finding was consistent with the tenets of the Technology Acceptance Model (TAM), which suggested that perceptions of ease of use significantly influence technology acceptance and usage behavior (Davis, 1989). Similar results have been reported in other studies within the context of educational technology, where ease of use has emerged as an important determinant of behavioral intention (Venkatesh et al., 2003; Radianti et al., 2020).

Attitude towards the Virtual Reality (VR) also demonstrated a significant positive effect ($B = 0.223$, $\beta = .234$, $t = 2.49$, $p = .015$), indicating that students with favorable attitudes were more likely to have the intention to adopt and utilize the technology. This finding was in line with prior studies that highlighted the role of attitude as a critical mediator in technology acceptance (Davis, 1989; Venkatesh et al., 2003).

In contrast, for this study, perceived usefulness (PU) was not a significant predictor ($B = -0.027$, $\beta = -.029$, $t = -0.38$, $p = .708$), suggesting that its direct role in shaping behavioral intention was less distinct within this specific sample. This result diverged from the traditional TAM Model framework findings, where perceived usefulness (PU) was typically a strong determinant of intention (Davis, 1989). Nevertheless, similar findings had been observed in certain educational technology studies, where ease of use and attitude outweighed usefulness, most likely due to a lack of students' prior exposure and comfort when immersing in digital learning environments during the learning process (Radianti et al., 2020).

Table 4: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	
		B	Std. Error	Beta	t
1	(Constant)	.260	.185		1.400
	perceived Usefulness	-.027	.071	-.029	-.375

perceived Ease of Use	.744	.091	.717	8.217	<.001
Attitude	.223	.090	.234	2.485	.015

a. Dependent Variable: Behavior Intention

Discussion

This study revealed the significant influence of attitude and perceived ease of use on students' behavioral intention to adopt immersive virtual reality and metaverse learning environments. Students generally held favorable views, with high average scores for perceived usefulness (PU) ($M=4.19$, $SD=0.68$) and attitude towards use (AT) ($M=4.21$, $SD=0.68$), consistent with existing technology acceptance literature (Davis, 1989; Mystakidis, 2022; Radianti et al., 2020). The strong score for perceived ease of use (PEU) ($M=3.92$, $SD=0.71$) also indicated that students found these platforms were easy to navigate, thus reinforcing their role in new learning technology acceptance (Davis, 1989).

Regression analysis also confirmed that these three factors collectively explained 81.2% of the variance in behavioral intention (BI). Perceived ease of use (PEU) was the most influential predictor ($B=0.744$, $p<.001$), highlighting its critical importance for interactive technology adoption, a finding supported by previous research in digital learning environments (Venkatesh et al., 2003; Radianti et al., 2020). Attitude (AT) also showed a significant positive relationship ($B=0.223$, $p=.015$), aligning with traditional TAM Model findings (Davis, 1989; Venkatesh et al., 2003).

Interestingly, Perceived Usefulness was not a significant direct predictor ($B=-0.027$, $p=.708$), which deviated from typical Technology Acceptance Model (TAM) results (Davis, 1989). Nevertheless, this outcome was aligned with other Virtual Reality (VR) and Metaverse studies where factors such as emotional factors, like attitude, were more impactful than usefulness, especially when learners already recognize the efficacy of digital tools (Radianti et al., 2020). This finding suggested that for highly interactive platforms, creating seamless user experiences and fostering positive emotional connections might be more crucial and important (Makransky, Terkildsen, & Mayer, 2019) for adoption than merely demonstrating functional benefits.

Ultimately, many of these findings highlighted how technology acceptance by humans is evolving, especially in the era of virtual reality (VR) and immersive learning in humans. Humans in general are very interested to learn from new, interesting environments and in this case, through virtual reality. From this study, it is also observed that the importance of virtual reality (VR) and metaverse designers and researchers in prioritizing the development of virtual technology and metaverse platforms that are both intuitively usable and emotionally engaging to promote sustainable engagement and adoption for the students.

5. Managerial Implications and Recommendations

This study provides key insights for educational institutions and developers regarding the effective implementation of immersive VR and metaverse platforms in academic settings. The important finding that perceived ease of use (PEU) was the dominant predictor of behavioral intention necessitates a strategic focus by managers and instructional designers on designing intuitive user-interface design and seamless interaction. Prioritizing investments in tailored training sessions and inherently user-friendly interfaces can significantly reduce cognitive demands, bolster user self-efficacy, and thereby promote wider technology uptake (Davis, 1989; Venkatesh et al., 2003).

Academic institutions should focus on designing intuitive platforms and fostering and fostering engaging learning experiences. But before full-scale implementation, evaluating students' readiness is essential. This can be done through a brief survey or any diagnostic tools assessing prior exposure to immersive technology, digital technology, and confidence level. Moreover, fostering a positive attitude towards these immersive platforms is indispensable. Integrating engaging interactive components, gamified experiences, and features that support social learning can enhance user engagement and stimulate prolonged utilization (Radianti et al., 2020). To further optimize the advantages offered by these technologies, comprehensive institutional backing—encompassing robust IT infrastructure, readily available access to necessary devices, and targeted digital literacy workshops—is critical for mitigating initial adoption barriers and building user proficiency (Wargadinata, 2025).

While perceived usefulness did not serve as a direct determinant in the present study, it remains imperative to articulate its benefits effectively. This involves clearly linking VR and metaverse learning opportunities with students' academic objectives and future career aspirations (Shen et al., 2024). Such an integrated approach empowers institutions to develop an ecosystem wherein immersive technologies evolve from exploratory tools into indispensable elements of the pedagogical landscape, thereby securing their enduring value and sustained integration.

For a similar study in the future, Slater and Sanchez-Vives (2016) proposed that future research should investigate additional external factors—such as trust, self-efficacy, and institutional support—to deepen insights into adoption behavior across varied educational settings. This is to be done because there are many factors out there that may influence the adoption of newer technology in all aspects of life. In this case, the using of virtual reality is used in many industries. Further, with the introduction of better, faster processor technology and the growth of artificial intelligence (AI), the learning process can be done in many interesting ways.

Conclusion

This study explored student acceptance of immersive Virtual Reality (VR) and Metaverse-integrated learning environments through the lens of the Technology Acceptance Model (TAM). The findings confirmed that perceived ease of use and attitude toward use significantly influenced students' Behavioral Intention, while Perceived Usefulness did not emerge as a significant predictor. These results suggest that ease of interaction and emotional engagement are more critical than functionality in shaping students' willingness to adopt immersive technologies in higher education.

From a theoretical perspective, this study reinforces the applicability of TAM in emerging educational technology contexts and highlights the evolving nature of technological acceptance, particularly the rising importance of affective factors. Practically, the findings underscore the necessity for educational institutions and developers to prioritize user-friendly interface design, emotional engagement strategies, and readiness assessments to ensure successful implementation.

However, this study is limited by its single-institution sample and gender imbalance, which may affect the generalizability of findings. Future research should incorporate more diverse populations and consider additional constructs such as trust, social influence, and self-efficacy. Additionally, comparative research across different cultural and institutional settings can deepen understanding of how immersive learning is accepted globally.

References

- Alzahrani, A. (2023). An Analysis of TAM in Understanding Faculty's Behavioral Intention to Use IoT. *International Journal of Educational Research and Innovation*, 19, 153–169.
- Bahaj, S. A. (2025). Students' Perception of Mobile Payment Application Using TAM Model: An Empirical Study in Saudi Arabia. *International Journal of Data and Network Science*, 9(1), 87–96. <https://doi.org/10.5267/j.ijdns.2024.12.005>
- Choung, H., David, P., & Ross, A. (2022). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human-Computer Interaction*, 39(6), 547–559. <https://doi.org/10.1080/10447318.2022.2050543>
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4th ed.). SAGE.
- Freina, L., & Ott, M. (2015). A Literature Review on Immersive Virtual Reality in Education: State of the Art and Perspectives. *Proceedings of eLearning and Software for Education (eLSE)*, 1, 133–141, "Carol I" National Defence University Publishing House.
- García, J. A. M., Gómez, C. G., López, A. T., & Schlosser, M. J. (2024). Applying the Technology Acceptance Model to Online Self-learning: A Multigroup Analysis. *Journal of Innovation & Knowledge*, 9(4), 100571. <https://doi.org/10.1016/j.jik.2024.100571>

- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis** (8th ed.). Cengage.
- Jerald, J. (2015). *The VR book: Human-centered Design for Virtual Reality*. ACM Books/Morgan & Claypool Publishers. <https://doi.org/10.1145/2792790>
- Johnson-Glenberg, M. C. (2018). Immersive VR and Education: Embodied Design Principles that include Gesture and Hand Controls. *Frontiers in Robotics and AI*, 5, 81. <https://doi.org/10.3389/frobt.2018.00081>
- Lee, K. (2021). Artificial Intelligence and Education: A Critical Review and Practical Implications. *Computers & Education: Artificial Intelligence*, 2, 100027. <https://doi.org/10.1016/j.caeai.2021.100027>
- Makransky, G., Terkildsen, T. S., & Mayer, R. E. (2019). Adding Immersive Virtual Reality to a Science Lab Simulation Causes More Presence but Less Learning. *Learning and Instruction*, 60, 225–236. <https://doi.org/10.1016/j.learninstruc.2017.12.007>
- Martin-García, A. V., Redolat, R., & Pinazo-Hernandis, S. (2022). Factors Influencing Intention to Technological Use in Older Adults: The TAM Model Application. *Research on Aging*, 44(7–8), 573–588. <https://doi.org/10.1177/01640275211063797>
- Milgram, P., & Kishino, F. (1994). A Taxonomy Of Mixed Reality Visual Displays. *IEICE Transactions on Information and Systems*, E77-D(12), 1321–1329.
- Musyaffi, A. M., Adha, M. A., Mukhibad, H., & Oli, M. C. (2024). Improving Students' Openness To Artificial Intelligence Through Risk Awareness And Digital Literacy: Evidence from A Developing Country. *Social Sciences & Humanities Open*, 10, 101442. <https://doi.org/10.1016/j.ssaho.2024.101442>
- Mystakidis, S. (2022). Metaverse. In *Encyclopedia of Education and Information Technologies*, (pp. 1–11). Springer. https://doi.org/10.1007/978-3-030-99021-0_160
- Nagy, S., & Hajdu, N. (2021). Consumer Acceptance of the Use of Artificial Intelligence in Online Shopping: Evidence from Hungary. *Amfiteatru Economic*, 23(56), 155–173. <https://doi.org/10.24818/EA/2021/56/155>
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory*, (3rd ed.). McGraw-Hill.
- Pallant, J. (2020). *SPSS Survival Manual: A Step-by-Step Guide to Data Analysis Using IBM SPSS* (7th ed.). McGraw-Hill Education.
- Pantelidis, V. S. (1993). Virtual Reality in Education. *Education and Information Technologies*, 1(1), 37–41. <https://doi.org/10.1007/BF00735634>
- Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A Systematic Review of Immersive Virtual Reality Applications for Higher Education: Design Elements, Lessons Learned, and Research Agenda. *Computers & Education*, 147, 103779. <https://doi.org/10.1016/j.compedu.2019.103779>
- Rosli, M. S., & Saleh, N. S. (2024). Predicting the Acceptance of Metaverse for Educational Purposes in Universities: A Structural Equation Model and Mediation Analysis of the Extended Technology Acceptance Model. *SN Computer Science*, 5(6), 688. <https://doi.org/10.1007/s42979-024-01968-4>
- Shen, M., Yu, L., Xu, J., Sang, Z., Li, R., & Yuan, X. (2024). Shaping the Future of Urban Mobility: Insights into Autonomous Vehicle Acceptance in Shanghai through TAM and Perceived Risk Analysis. *Transportation Research Part F: Traffic Psychology and Behavior*, 99, 227–242. <https://doi.org/10.1016/j.trf.2024.04.010>
- Shen, X., Zhang, Y., Liu, J., & Li, Z. (2024). The Role of Perceived Usefulness and Perceived Ease of Use in Shaping VR Adoption in Higher Education. *Educational Technology & Society*, 27(1), 127–142. <https://www.jstor.org/stable/48123856>
- Slater, M., & Sanchez-Vives, M. V. (2016). Enhancing Our Lives with Immersive Virtual Reality. *Frontiers in Robotics and AI*, 3, 74. <https://doi.org/10.3389/frobt.2016.00074>
- Tabachnick, B. G., & Fidell, L. S. (2019). *Using Multivariate Statistics*, (7th ed.). Pearson.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Wargadinata, E. (2025a). Rural AI Acceptance of Artificial Intelligence Technology on Stunting Prevalence Reduction. *Human Resource Management Academic Research Society (HRMARS)*, 12(11), 2863.
- Wargadinata, W. (2025b). Infrastructure Readiness and Digital Literacy as Predictors of AI Adoption in Rural Healthcare. *Journal of Information Systems for Development*, 31(1), 14–29.
- Wibowo, A., Saptono, A., Narmaditya, B., Effendi, M., Mukhtar, S., Suparno, S., & Mohd Shafiai, M. H. (2024). Using the Technology Acceptance Model to Investigate Digital Business Intention Among Indonesian Students. *Cogent Business & Management*, 11, 2356789. <https://doi.org/10.1080/23311975.2024.2356789>