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| RESEARCH ARTICLE

Construction and Practical Research on Intelligent Management Model of Training Rooms in Higher Vocational Colleges Driven by Artificial Intelligence

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| ABSTRACT
China's vocational colleges have a hard time with room management, mainly due to ineffective scheduling, unused resources and not enough technology. Artificial intelligence is providing a useful answer to these difficulties with intelligent automation, predictive maintenance and continuous tracking. The study develops and confirms a model to guide smart management in training rooms of higher vocational colleges, focusing on how AI infrastructure, institutional support, digital literacy, system integration and readiness for change together affect management. The data came from 450 responses to questionnaires distributed to staff members in vocational colleges across China. Constructs were assessed with items that have been proven valid using the Likert scale. With SmartPLS 4.0, direct, mediating and moderating effects were tested for six constructs: AI-Based Infrastructure Readiness (AIR), Administrative Support for Digital Innovation (ASDI), User Digital Literacy (UDL), System Integration Effectiveness (SIE), Organizational Change Readiness (OCR), and Training Room Management Efficiency (TRME). AIR, ASDI and UDL impact SIE greatly and SIE in turn strongly influences TRME. SIE links how these factors impact TRME. OCR affects these connections in two ways, whether it encourages or reduces them. Both SIE and TRME are explained by the model to the extent of 42.7% and 44.6%, respectively. All three components are important for achieving the best results from AI management—leaders should be sure they all match. This research presents a new, scientifically proven system for managing facilities in vocational education.

| KEYWORDS

Artificial intelligence, vocational education, training room management, system integration, digital literacy, organizational readiness, SmartPLS, China

| ARTICLE INFORMATION

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1. Introduction

Artificial intelligence (AI) has evolved quickly which has led to modern digital transformation in several sectors, among them education. By using AI, higher vocational colleges can enhance their facility management, make operations more efficient, improve the way students learn and support decisions based on data(Aldous & Ismail, 2025; Bakeer, 2024). The failure of most traditional training rooms to use artificial intelligence often results in errors in scheduling, poor space management, unplanned maintenance and poor teamwork between leaders and administrators (Barashkin, Nurguatova, Kalashnikov, Taktasheva, & Tupysev, 2023). As a result, organizations dealing with resource shortages and too much responsibility have a harder time offering quality technical and vocational training.

Using artificial intelligence in management systems makes these problems easier to handle. AI makes it possible for smart homes to efficiently schedule, track usage, control the environment and plan maintenance, using machine learning, facial recognition, IoT and real-time analytics Koukaras et al. (2025). Adding AI-based systems to the overall digital infrastructure in vocational colleges can result in better-managed training rooms, lower costs and a top-level of service for both students and instructors (Glover, Li, Naveh, & Gross, 2017; Sayari, 2025).

It takes a complete strategy, using technology, administrative help and users willing to adopt, to go from traditional to intelligent management models. Aprilia, Sultoni, and Timan (2024) highlight that, along with Galanti and Fantinelli (2024), administrative leaders can help accelerate digital change and use AI tools more widely. In addition, for digital transformation to happen, users must be prepared. People in the education system must have enough digital knowledge to get the most out of AI tools (MANHA, RAKBUMRUNG, JANKAWEEKUN, & SANG-ON, 2024; Nikou, De Reuver, & Mahboob Kanafi, 2022). A lack of this basic skill could stop businesses from enjoying the advantages of AI.

How ready an organization is to accept change is a key element in success with new technology. If a company encourages open communication, developing its workforce and involves all stakeholders, it will more successfully use the benefits of AI (Kasana, 2021; Weiner, 2020). Therefore, Organizational Change Readiness (OCR) provides an effective method for looking at how ready a school is for AI-driven progress.

People are interested in using AI in education, yet there are still very few scientific studies that examine managing physical educational spaces such as training rooms in vocational colleges. AI's effect on instruction, student activities and assessment has received most study attention, yet little is known about its impact on operational infrastructure. This research fills the gap by introducing and testing an intelligent model for managing training rooms using structural equation modeling with SmartPLS.

We propose considering AIR, ASDI, UDL, SIE, OCR and TRME as the main constructs of the model. These relationships are supported by both theories and what researchers find in current literature (Domingues, Sampaio, & Arezes, 2017; Shen et al., 2010). AI-Based Infrastructure Readiness refers to how well an organization has the technology needed—hardware, software and network tools—to incorporate AI (Pawlowski & Apolinarski, 2024). Top leaders must agree to support, assign funds and set up policies to oversee ongoing progress of digital initiatives (Galanti & Fantinelli, 2024). To use intelligent systems well, institutions need members who are digitally literate to use these tools effectively (Nikou et al., 2022; Shahzad, Khan, & Iqbal, 2024).

System Integration Effectiveness focuses on how easily the AI-based management system partners with the systems, structures and technologies already in use (Shen et al., 2010). Organizational Change Readiness shows the mental and cultural preparedness of a school to accept new technologies (Weiner, 2020). Training Room Management Efficiency tests the operational success of training room systems by checking appointment accuracy, energy savings, equipment use and user comfort.

When these constructs are added, the study explains the relationships between technological, organizational and human factors. Researchers' discoveries support policy-makers, senior staff and technology experts in designing and using AI for managing schools effectively. As international institutions and governments work towards the UN Sustainable Development Goals and their own digital education strategies, this study helps by analyzing how smart campus models can be applied.

After setting the framework, this paper reviews existing studies that connect each construct and explain their theoretical connections. Furthermore, the review proposes hypotheses using both empirical and conceptual work. Subsequently, the authors include a section on how they collected data and conducted their analyses. In the results section, we discuss the outcome of the path analysis and in the discussion, we link these results to earlier research. The conclusion of the paper offers useful tips for application, points out research limits and highlights possible future areas of interest.

2. Literature Review

More and more, it is considered important to include AI in educational management systems, rather than an optional addition (Sposato & Dittmar, 2025). The use of AI-based management models in classrooms or labs is achievable only when technology is supported by changes in the organization and by the full engagement of users. This section discusses what the existing studies say about each of the six constructs: Assessing AI Technology Infrastructure – known as AIR, Practical support for new technology from administration (ASDI), User Digital Literacy (UDL), System Integration Effectiveness (SIE), Organizational Change Readiness (OCR) and Training Room Management Efficiency (TRME).

AI-Based Infrastructure Readiness (AIR)

All intelligent systems are built on top of a solid infrastructure. AIR includes the hardware needed for AI (such as sensors and servers), the software used for it and the necessary networks to manage training rooms intelligently. Sayari's study (Sayari, 2025) and the research by Koukaras et al. (2025) point out that strong digital frameworks raise an institution's chances of adopting AI successfully. For this reason, it is proposed that:

H1: AIR is positively associated with SIE.

H2: AIR is positively linked to the efficiency of how TRME is handled.

Administrative Support for Digital Innovation (ASDI)

The success and continuation of technological change largely depend on administrative commitment and a smart strategic vision. Leadership, they argue, encourages digital innovation by investing resources, determining rules and inspiring faculty and staff. In emergency settings, having policy support is important for digital transformation, as Galanti and Fantinelli (2024) have found. As a result, we propose the following as possible explanations:

H3: ASDI plays a significant role in improving advantages from effective system integration.
H4: ASDI plays a positive role in increasing Training Room Management Efficiency (TRME).
User Digital Literacy
Leadership and strong infrastructure are essential, but so too are the digital abilities of everyone in the institution. As Nikou et al. (2022) explain, UDL refers to how learners use their mind, technology and behaviors to successfully use digital systems. MANHA et al. (2024) point out that digital literacy plays a key role in how administrative staff perform at smart campuses. As a result, we suggest this approach:
H5: The influence of user digital literacy on system integration effectiveness is positive.
H6: The ability of users to use the Internet well (UDL) improves the effectiveness of training room management (TRME).
System Integration Effectiveness (SIE)
SIE means matching AI systems with existing procedures such as online scheduling, record-keeping of maintenance and monitoring for access control. Shen et al. (2010) point out that successful integration comes from having compatible systems, a good user interface and interoperability. In healthcare, (Glover et al., 2017) find that how well integration is achieved usually leads to significant improvements in outcomes.
H7: System Integration Effectiveness is related to how well Training Room Management works.
More importantly, since SIE connects AI information with operations, it is believed to function as a mediator.
H8: The relationship between AI-Based Infrastructure Readiness (AIR) and Training Room Management Efficiency (TRME) is mediated by System Integration Effectiveness (SIE).
H9: System Integration Effectiveness (SIE) acts as a link between Administrative Support for Digital Innovation (ASDI) and how well Training Room Management Efficiency (TRME) is carried out.
H10: For every connection, User Digital Literacy (UDL) and Training Room Management Efficiency (TRME) require System Integration Effectiveness (SIE).
Organizational Change Readiness
For Weiner (2020), change readiness means a group's ability and motivation to take on transformation activities. In OCR, cultural openness, flexible structures and a robust institution are important. Both Kasana (2021) and Zelenkov (2018) point out that the effect of digital strategies on performance is strongly moderated by an organization’s readiness for change, especially in times of technological disruption. Because of this, we suggest:
H11: The ready level of managers for organizational change is found to positively affect Training Room Management Efficiency.
H12: The relationship between AI-Based Infrastructure Readiness (AIR) and Training Room Management Efficiency (TRME) is positively affected when Organizational Change Readiness (OCR) is present.
H13: Suggests that training room management efficiency is improved when there is high organizational change readiness (OCR), when administrative support for digital innovation (ASDI) is present.
H14: Organizational change readiness positively moderates the relation between User Digital Literacy and Training Room Management Efficiency.
The relationships among the suggested constructs can be clearly seen in the diagram below.

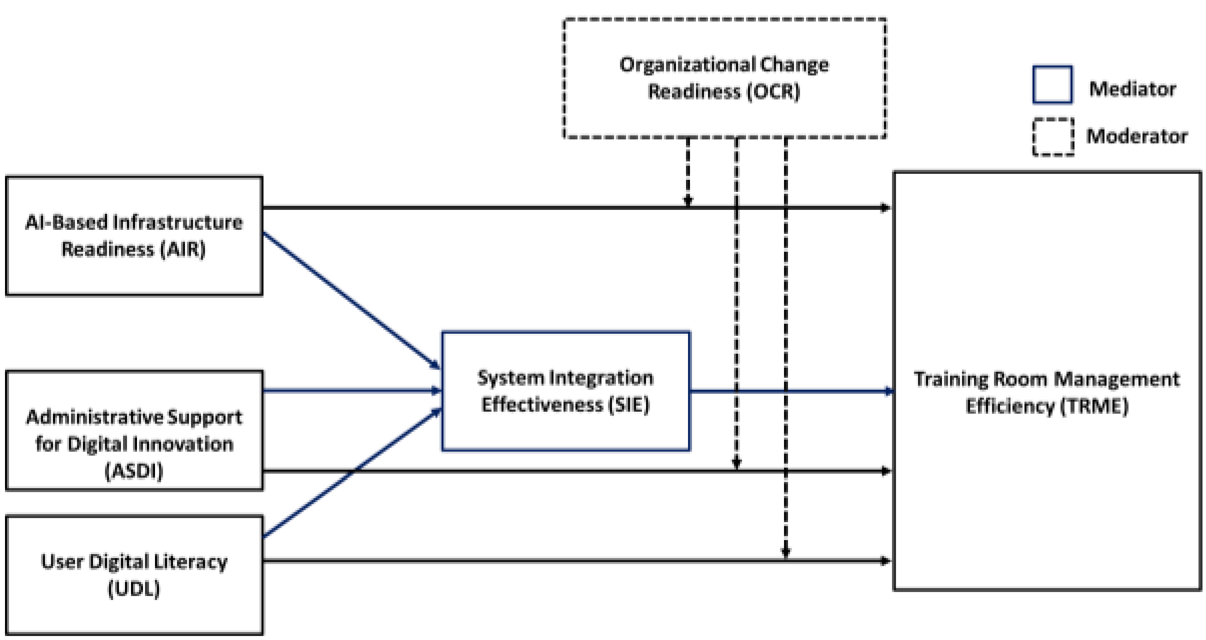

Figure 1: Conceptual Framework of the Study

Training Room Management Efficiency (TRME)

TRME is listed as the dependent variable and reflects important performance measures such as how resources are utilized, accuracy of schedules, how much energy is used and users' level of satisfaction. Research done by Barashkin et al. (2023) and Lestari, Rahmayana, and Agustiana (2025) shows that adding AI to education greatly improves operations. It shows that TRME is a key aim for using AI in higher vocational colleges.

Based on what these experts (Koukaras et al., 2025; Sayari, 2025) discuss, AI infrastructure and wireless technologies are foundational to the transformation of education systems. They also reveal that AI helps organizations and governments respond better in emergencies and keeps institutions resilient.

In their 2025 case study in Indonesia, Lestari and Rahmayana suggest that AI can improve how effective and flexible learning can be, mainly in religious education classes. Meanwhile, Galanti and Fantinelli (2024) from Italy present data that shows successful digital transformation in learning is linked to strong leadership.

MANHA et al. (2024) and Nikou et al. (2022) cover the effects of employees' skills and the firm's digital readiness on operations and adoption of technology. The results back up the idea of User Digital Literacy (UDL) in the model.

Based on the views of Kasana (2021), Weiner (2020), and Zelenkov (2018), change readiness and knowledge management need to be established first before AI is successfully implemented in organizations. These predictions fit with the definition of the moderator construct Organizational Change Readiness (OCR).

The studies of Glover et al. (2017) and Shen et al. (2010) supply useful data and analyses on both the pros and cons of system integration. Because of their findings, we now see that SIE should be a mediating and outcome variable in the model.

Supporting international studies that relate to the conceptual model for intelligent training room management in higher vocational colleges are shown in the table. Methods used in these studies include empirical, conceptual, theoretical, survey and review approaches, all pointing to the role of AI infrastructure, leaders, user knowledge and readiness of organizations in supporting successful implementation of AI tools in schools. Besides, the table proves that AI brings many benefits at once, making sense of the six central ideas discussed in the study: AIR, ASDI, UDL, SIE, OCR and TRME. It verifies that for AI-driven training room use to work well, you need technology, skilled staff, thoughtful planning and a ready willingness for change among staff.

Table 1: Literature Review Matrix

Author (Year)	Year	Country	Type of Study	Key Findings
(Sayari, 2025)	2025	Global	Review	AI infrastructure is crucial for enabling smart educational environments
(Koukaras et al., 2025)	2025	Greece	Conceptual/Framework	Wireless networks and AI improve resource allocation in education
(Aldous & Ismail, 2025)	2025	Global	Conceptual	AI enhances emergency response and resilience in educational institutions
(Lestari et al., 2025)	2025	Indonesia	Case Study	AI supports adaptive, efficient learning in modern religious education settings
(Galanti & Fantinelli, 2024)	2024	Italy	Empirical	Strategic leadership drives digital innovation and learning effectiveness
(MANHA et al., 2024)	2024	Thailand	Survey	Digital skills are directly linked to operational performance of staff
(Barashkin et al., 2023)	2023	Russia	Empirical	Digital technologies enhance training process efficiency and engagement
(Nikou et al., 2022)	2022	Finland/Netherlands	Quantitative	Digital literacy boosts adoption of technology in the workplace
(Kasana, 2021)	2021	India	Survey	Change readiness influences success of technology-led initiatives
(Weiner, 2020)	2020	USA	Theoretical	Organizational readiness is essential for effective change implementation
(Zelenkov, 2018)	2018	Russia	Quantitative	Knowledge management and readiness affect institutional performance
(Glover et al., 2017)	2017	USA	Case Study	Human-systems integration enhances process quality and care outcomes
(Shen et al., 2010)	2010	Canada	Review	Integration challenges exist in AI-adoption across institutional workflows

3. Data and Methodology

3.1 Research Design

A quantitative, cross-sectional and explanatory approach was selected to examine how AI infrastructure, preparedness among officials and users and how well organizations adapt to change impact the management of training rooms in vocational colleges. To test the study's main objectives and check how different constructs are related to each other, a SEM approach using SmartPLS was seen as the most suitable. Because of this design, multiple dependent relationships can be studied together and it is useful for research that uses latent variables through multiple items.

3.2 Population and Sampling

The target group for the study is faculty, administrative workers and IT experts from China's higher vocational colleges who are either already or soon going to use AI in their campus administration. As a full listing of internet users is unavailable and understanding digital systems is necessary, purposive sampling was used. To be included, participants needed to know how to use institutional technology, run training rooms or play a part in administration for digital changes. A total of 450 valid replies were gathered and run through PLS-SEM which met the minimum sample size standard advised by Hair, Risher, Sarstedt, and Ringle (2019).

3.3 Collection of Data

We collected primary data using a questionnaire that participants completed either online or in person from March to May 2024. The questionnaire was developed in English and then put into simplified Chinese by a forward-backward method to maintain correct use of words. Before taking part, people were informed about the research and asked if they agreed to participate. Because of the help and directions from administrative people at the chosen institutions, data was collected effectively and sent to the right target. Participants were reminded and their answers were kept anonymous to protect their privacy.

3.4 Measurement of Variables

Every aspect of the model was evaluated through the use of multi-item Likert-type scales that ran from 1 (strongly disagree) to 5 (strongly agree). We used items from instruments that were already validated by others to check their suitability.

Table 2: Constructs and the Items

Construct	Item
AI-Based Infrastructure Readiness (AIR) Adapted from (Vial, 2021; Westerman, Calméjane, Bonnet, Ferraris, & McAfee, 2011)	AIR1: Our institution has the necessary hardware (e.g., sensors, cameras) to support AI-based training room management.
	AIR2: We have a stable network and data infrastructure to support intelligent facility systems.
	AIR3: AI applications (e.g., facial recognition, occupancy tracking) are already partially integrated.
	AIR4: There are dedicated software platforms for AI-based classroom or lab scheduling.
	AIR5: Our institution has invested in IoT devices to support real-time monitoring of training rooms.
	AIR6: The infrastructure is scalable for future AI enhancements in facility management.
Administrative Support for Digital Innovation (ASDI) Adapted from (Lestari et al., 2025)	ASDI1: Senior management strongly supports the implementation of AI in operational areas.
	ASDI2: Administrators are willing to allocate resources for digital innovation projects.
	ASDI3: Policies at our institution actively encourage AI integration in facility management.
	ASDI4: Leaders frequently communicate the benefits of using AI-driven systems.
	ASDI5: There is a strategic plan to embed digital technologies in infrastructure management.
User Digital Literacy (UDL) Adapted from (Eshet, 2004; Ng, 2012)	UDL1: I am confident in using AI-supported platforms and dashboards.
	UDL2: I can troubleshoot or adapt to changes in digital facility management systems.
	UDL3: I understand how AI-based systems (e.g., auto-scheduling) function.
	UDL4: I regularly use digital tools to manage tasks related to training room

	usage.
	UDL5: I can independently operate technology installed in AI-enabled training rooms.
	UDL6: I actively seek training or updates related to digital tools in my institution.
System Integration Effectiveness (SIE) Adapted from (DeLone & McLean, 2003; Sedera, Gable, & Chan, 2004)	SIE1: The AI system integrates seamlessly with our current training room operations.
	SIE2: The AI-based management system reduces the need for manual intervention.
	SIE3: Real-time data from training rooms is effectively captured and used by the system.
	SIE4: All subsystems (e.g., scheduling, lighting, access control) are well-coordinated through the AI platform.
	SIE5: The system is user-friendly and aligns well with existing workflows.
Organizational Change Readiness (OCR) Adapted from (Armenakis, Harris, & Mossholder, 1993; Holt, Armenakis, Feild, & Harris, 2007)	OCR1: Staff and faculty are generally open to adopting new AI technologies.
	OCR2: Our institution actively prepares employees for digital transformation.
	OCR3: Change initiatives are communicated clearly and effectively.
	OCR4: There is a culture of innovation and experimentation in our organization.
	OCR5: Resistance to change is low when digital systems are introduced.
Training Room Management Efficiency (TRME) (Parasuraman, Zeithaml, & Malhotra, 2005); adapted to smart facility context	TRME1: The AI system improves the scheduling efficiency of training rooms.
	TRME2: Room utilization rates have increased since implementing the intelligent system.
	TRME3: Maintenance issues are identified and resolved faster with the AI-based system.
	TRME4: The system minimizes conflicts in room bookings.
	TRME5: Environmental controls (e.g., lighting, air) are optimized automatically.
	TRME6: Overall, the management of training rooms is more efficient due to AI integration.

Before using any items, they were tried out on a pilot sample to make sure they were easy to understand and reliable.

3.5 Methods of Analyzing Data

Analysis of the data was performed with PLS-SEM in SmartPLS version 4.0. The choice of PLS-SEM came from its ability to work with complex models that include multiple mediated and moderated paths and from its strong performance with minimal sample size. The health measurement model was reviewed by testing its reliability, validity and outer loadings. Through bootstrapping using 5,000 resamples, I obtained the path coefficients, t-statistics and p-values in the structural analysis. The amount of variance explained by different predictors was observed by examining the R-squared values. Moderation effects were examined with interaction variables and mediation was analyzed by indirect effect tests.

3.6 Ethical Considerations

This research was done according to ethical guidelines for social science studies. Everyone in the study was given details about the objectives, their option to refuse to participate and the protected handling of their answers. The procedure began only after we got participants' informed consent. No one was required to take part and no information that could identify a person was collected. The lead researcher's internal ethics review board reviewed and accepted the protocol for the research. The data obtained was used just for learning purposes and was kept securely to guard participants' confidentiality.

4. Results

4.1 The Results of the Convergent Validity Test

In Table 3, results from the validity test in SmartPLS can be observed. Convergent validity is measured by how aligned different indicators of one construct are and this alignment is often checked using item loadings, Cronbach's Alpha, Composite Reliability (CR) and Average Variance Extracted (AVE).

Ai powered system readiness known as AIR shows item loadings between 0.797 and 0.853. A Composite Reliability of 0.927 and a Cronbach's Alpha of 0.906 show that AIR is highly reliable and an AVE of 0.68 indicates good convergent validity. Administrative Support for Digital Innovation (ASDI) has similarly good levels of reliability and validity: its loadings are 0.833 to 0.864, with an Alpha of 0.904, CR of 0.929 and AVE of 0.723.

The loadings of Organizational Change Readiness (OCR) vary from 0.799 to 0.855, while its reliability has Alpha of 0.886, CR of 0.916 and AVE of 0.687, all demonstrating good validity. All measures of SIE—loadings from 0.844 to 0.859, Alpha of 0.874, CR of 0.914 and AVE of 0.726—are above the thresholds needed.

The results show good internal reliability and measuring accuracy, as TRME loads between 0.828 and 0.879, while Alpha is 0.905, CR is 0.930 and AVE is 0.725. Finally, User Digital Literacy consistently loads between 0.818 and 0.836 on all of its items, showing good construct representation, measured with Alpha (0.910), CR (0.930) and AVE (0.690).

All in all, the results confirm that every construct in the model shows strong convergence with others. Since all loadings are over 0.70, the Composite Reliability is greater than 0.90 for each construct and all AVE are above 0.50, data show that all variables are reliably and validly measured.

Table 3: Convergent Validity Test

Constructs	items	Loading	Alpha	CR	AVE
AIR	AIR1	0.853	0.906	0.927	0.68
	AIR2	0.812			
	AIR3	0.818			
	AIR4	0.797			
	AIR5	0.839			
	AIR6	0.829			
ASDI	ASDI1	0.849	0.904	0.929	0.723
	ASDI2	0.833			
	ASDI3	0.852			
	ASDI4	0.854			
	ASDI5	0.864			
OCR	OCR1	0.799	0.886	0.916	0.687
	OCR2	0.849			
	OCR3	0.827			
	OCR4	0.813			
	OCR5	0.855			
SIE	SIE1	0.854	0.874	0.914	0.726
	SIE2	0.85			
	SIE3	0.844			
	SIE4	0.859			
TRME	TRME1	0.848	0.905	0.93	0.725
	TRME2	0.828			
	TRME3	0.845			
	TRME4	0.858			
	TRME5	0.879			
UDL	UDL1	0.836	0.91	0.93	0.69
	UDL2	0.832			
	UDL3	0.818			
	UDL4	0.829			
	UDL5	0.836			
	UDL6	0.834			

4.2 Discriminant Validity Assessment through Heterotrait-Monotrait Ratio

The values in Table 4 are called Heterotrait-Monotrait (HTMT) ratios and they are applied to check discriminant validity in structural equation modeling. Confirming discriminant validity confirms that each factor being studied is different from the others. The generally accepted rule is that if HTMT is below 0.85, then the difference between two constructs is satisfactorily discriminant.

AI-Based Infrastructure Readiness (AIR) has an HTMT ratio of only 0.045 or lower with each construct that was measured except for UDL which is 0.056. The values reveal that AIR is clearly off from the other constructs in the model.

The remaining constructs also have significant distinguishing properties from ASDI, recording 0.239 with OCR, 0.296 with SIE, 0.253 with TRME and 0.129 with UDL. Each value is at least half a standard deviation below the 0.85 limit.

OCR is more strongly related to Certainty in Strategy (SIE) and Task Confidence (TRME) than to other constructs, with 0.617 and 0.476, respectively. But the values remain within acceptable limits which indicates that OCR has enough differences from the other constructs.

In the table, System Integration Effectiveness has the highest HTMT value of 0.617 for OCR and 0.606 for TRME and since they fall short of the cutoff, both show adequate discrimination. Its ASDI, AIR and UDL values of 0.296, 0.479 and 0.438 also confirm its discriminant status.

TRME shows that all constructs, including UDL, are valid based on Discriminant Validity, with HTMT = 0.302. UDL showed very low HTMT values of 0.056 with AIR and 0.438 with SIE, confirming that it is a separate construct.

In short, all of the HTMTs are below 0.85, confirming that each construct in the model is distinct from every other construct.

Table 4: HTMT Ratio

	AIR	ASDI	OCR	SIE	TRME	UDL
AIR						
ASDI	0.045					
OCR	0.201	0.239				
SIE	0.479	0.296	0.617			
TRME	0.289	0.253	0.476	0.606		
UDL	0.056	0.129	0.29	0.438	0.302	

Fornell-Larcker criterion results which are commonly used to judge structural equation modeling discriminant validity, are found in Table 4. This criterion implies that for all constructs, the AVE for each construct's square root—as shown in bold along the diagonal—should surpass the level of correlation between the construct and every other in the model. In other words, this guarantees that one construct's variance is stronger with its indicators than with different constructs.

The result shows that AI-Based Infrastructure Readiness (AIR) is a reliable measure, with its square root (0.825) proving to be larger than each correlation it has with ASDI (–0.02), OCR (0.183), SIE (0.43), TRME (0.265) and UDL (0.038).

The correlation between all other constructs and ASDI (AIR, OCR, SIE, TRME and UDL) are smaller than the square root of AVE, showing that ASDI is reasonably different from the other constructs on the instrument.

Its diagonal value which is 0.829, is higher than the correlations with AIR (0.183), ASDI (0.214), SIE (0.545), TRME (0.429) and UDL (0.262), fulfilling the Fornell-Larcker rule.

The square root of AVE for System Integration Effectiveness (SIE) is 0.852 which is higher than the correlations seen with the remaining constructs: AIR (0.43), ASDI (0.263), OCR (0.545), TRME (0.539) and UDL (0.391). The findings show that SIE stands out as its own unique concept compared to the other ones.

The benchmark for Training Room Management Efficiency (TRME) is achieved, as the square root of AVE comes out to 0.852. This has a greater correlation with TEV (0.618) than with AIR (0.265), ASDI (0.231), OCR (0.429), SIE (0.539) and UDL (0.276).

In addition, User Digital Literacy (UDL) is higher than all the other constructs on its diagonal, confirming that it is not closely related to any other variables: AIR (0.038), ASDI (–0.117), OCR (0.262), SIE (0.391) and TRME (0.276).

Table 5: Fornell Larcker

	AIR	ASDI	OCR	SIE	TRME	UDL
AIR	0.825					
ASDI	-0.02	0.85				
OCR	0.183	0.214	0.829			
SIE	0.43	0.263	0.545	0.852		

TRME	0.265	0.231	0.429	0.539	0.852	
UDL	0.038	-0.117	0.262	0.391	0.276	0.831

The cross loadings shown in Table 6 provide another way to see if the factors are distinct in structural equation modeling. The score of an item should be more closely connected with its intended construct than with any other construct. The findings prove that the chosen item is mainly linked to the desired construct and not to other constructs.

All six items (AIR1 to AIR6) for the construct AIR-Based Infrastructure Readiness (AIR) load strongly onto the construct, with scores ranging from 0.797 to 0.853. There is much less association between AIR items and ASDI, OCR, SIE, TRME and UDL, suggesting that they each measure exactly what they intend to measure.

ASDI is shown to be present by how highly the items for ASDI1 through ASDI5 load on the construct, with values from 0.833 to 0.864. The weak relationships shown with other constructs, including a few negative ones, prove that these constructs are valid.

Of the five OCR items (OCR1 to OCR5), they load highest on OCR (range 0.799 to 0.855) and much less on all the other constructs. Even though a few of the items overlap trivially with other constructs, their highest link is with CI, indicating a good degree of discriminant validity.

All four items for SIE have high and similar loadings between 0.844 and 0.859 which are higher than their correspondences with OCR and TRME. It points to the idea that the indicators are in line with what we call system integration.

Each of the five items has a strong individual positive relationship with its construct (ranging from 0.828 to 0.879) and a lower and mostly negative relationship with the rest. While both the SIE and OCR items have some correlation with SES, none of them loads higher on SES than they do on their main construct.

Moreover, the six User Digital Literacy (UDL) questions (UDL1 to UDL6) had the highest loadings on UDL, ranging between 0.818 and 0.836. The findings indicate that items in the UDL scale are not as closely linked to SIE, OCR and TRME compared to the other scales, confirming that UDL forms a unique construct.

Table 6: Cross Loadings

	AIR	ASDI	OCR	SIE	TRME	UDL
AIR1	**0.853**	0.003	0.160	0.395	0.230	0.058
AIR2	**0.812**	-0.019	0.150	0.379	0.263	0.023
AIR3	**0.818**	-0.012	0.147	0.360	0.201	0.056
AIR4	**0.797**	-0.044	0.114	0.313	0.171	0.037
AIR5	**0.839**	-0.002	0.160	0.321	0.198	0.008
AIR6	**0.829**	-0.027	0.167	0.348	0.234	0.005
ASDI1	0.005	**0.849**	0.197	0.238	0.158	-0.106
ASDI2	-0.057	**0.833**	0.145	0.213	0.163	-0.064
ASDI3	-0.012	**0.852**	0.213	0.235	0.219	-0.101
ASDI4	0.023	**0.854**	0.160	0.209	0.220	-0.099
ASDI5	-0.045	**0.864**	0.192	0.224	0.212	-0.124
OCR1	0.151	0.151	**0.799**	0.417	0.326	0.185
OCR2	0.205	0.143	**0.849**	0.493	0.378	0.231
OCR3	0.121	0.213	**0.827**	0.418	0.325	0.154
OCR4	0.117	0.187	**0.813**	0.430	0.347	0.290
OCR5	0.156	0.197	**0.855**	0.490	0.395	0.221
SIE1	0.334	0.238	0.503	**0.854**	0.460	0.313
SIE2	0.370	0.189	0.430	**0.850**	0.475	0.357
SIE3	0.364	0.241	0.477	**0.844**	0.439	0.310
SIE4	0.396	0.231	0.448	**0.859**	0.462	0.352
TRME1	0.222	0.175	0.364	0.447	**0.848**	0.213
TRME2	0.213	0.204	0.333	0.459	**0.828**	0.266
TRME3	0.238	0.193	0.324	0.450	**0.845**	0.232
TRME4	0.212	0.211	0.395	0.482	**0.858**	0.243

TRME5	0.244	0.198	0.408	0.457	**0.879**	0.222
UDL1	0.064	-0.102	0.217	0.343	0.222	**0.836**
UDL2	-0.020	-0.105	0.211	0.315	0.204	**0.832**
UDL3	0.075	-0.116	0.212	0.334	0.210	**0.818**
UDL4	0.029	-0.055	0.227	0.329	0.286	**0.829**
UDL5	0.046	-0.096	0.22	0.32	0.231	**0.836**
UDL6	-0.01	-0.115	0.219	0.308	0.217	**0.834**

4.3 Measurement Model

Both the measurement and structural model in the SmartPLS diagram display good statistical performance and fit the theory. Outer loadings for all observed variables (items) record between 0.797 and 0.879, indicating a strong ability of each item to measure the construct. As a result, we can say that each combination of items effectively measures its matching latent construct.

According to the structural model, various constructs are related. Each of AIR, ASDI and UDL contribute to increasing SIE, with path coefficients at 0.421, 0.320 and 0.413. It is clear from the results that successful AI integration for room management needs both tech support and staff and company readiness.

Effective System Integration (SIE) greatly improves Training Room Management Efficiency (TRME), as shown with a path coefficient of 0.354. Even so, AIR, ASDI and UDL remain important for TRME, but their effects are slightly muted by SIE, since all three have smaller coefficients, about 0.09. There is evidence of partial mediation since system integration is directly responsible for the link from infrastructure, support and literacy to operating outcomes.

There is clear evidence that Organizational Change Readiness (OCR) affects the dynamics of the relationships described. In addition to enhancing TRME (0.169), OCR affects all the relationships between AIR, ASDI and UDL and TRME through interaction terms. Each moderation path (0.208 for OCR × AIR, 0.198 for OCR × ASDI and 0.173 for OCR × UDL) is statistically significant, indicating that if a system is prepared culturally and structurally, the benefits of technology and user readiness on performance increase further.

Both system integration (0.427) and training room efficiency (0.446) are explained by a meaningful part of the model's variance. These findings suggest that the predictors explain the outcome constructs well and that each predictor adds value to the model.

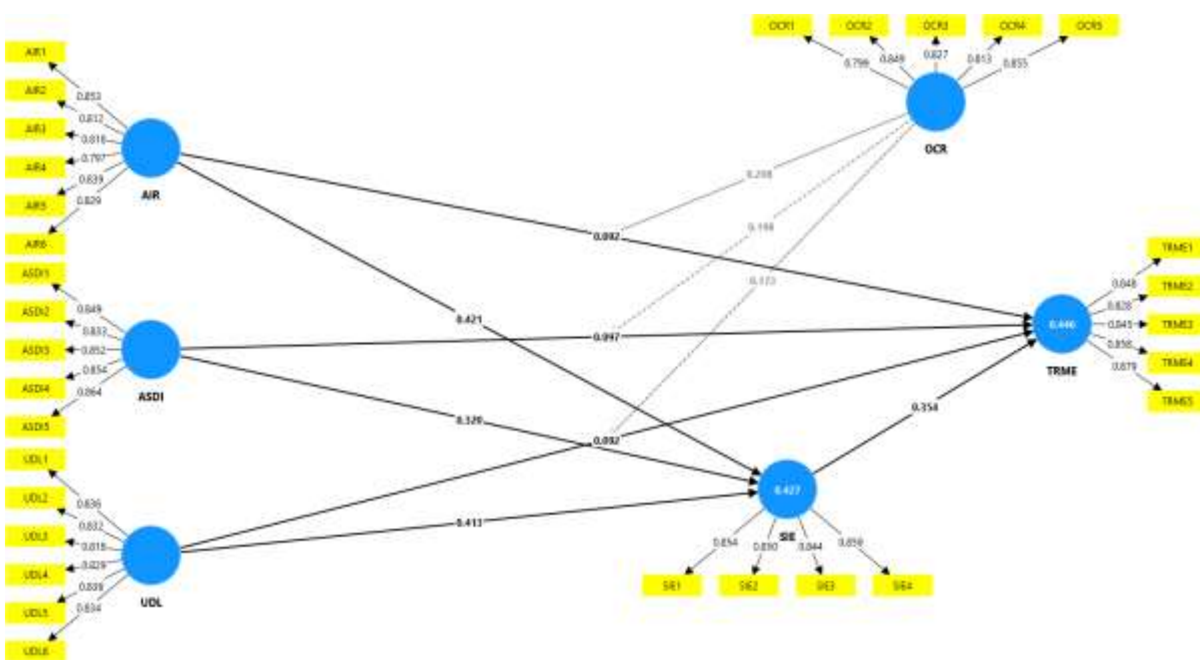

Figure 2: Measurement Model

4.4 Path Analysis

Table 7 shows the results from using SmartPLS which estimate how the relationships described in the structural model are direct, moderating and mediating. In the table, the original sample estimates (O), means (M), standard deviations (STDEV), t-statistics and p-values are shown for every hypothesized path.

AI-Based Infrastructure Readiness (AIR) is strongly associated with System Integration Effectiveness (SIE), with a 0.421 path coefficient and a highly significant p-value of 0.000. It suggests that increased infrastructure readiness plays a positive role in promoting system integration.

There is a clear relationship from AIR to TRME that matters, although it is a smaller influence (0.092).

Administrative Support for Digital Innovation (ASDI) is an important factor contributing to SIE ($r = 0.320$; $t = 8.969$; $p < 0.001$) and to improvement of the organization's tech-related operations (TRME; $r = 0.097$; $t = 2.361$; $p = 0.018$).

Organizational Change Readiness (OCR) has a positive impact on TRME and a high t-statistic and extremely low p-value show that TRME benefits directly from being ready for change within organizations.

TRME values are affected by SIE with a coefficient of 0.354, a t-statistic of 6.495 and a p-value of 0.000. It reveals that an organization's AI systems greatly impact their management capabilities.

Having Digital Literacy skills allows users to improve SIE (0.413; $t = 11.899$; $p < 0.001$) and TRME (0.092; $t = 2.069$; $p= 0.039$).

The interaction terms between OCR and other variables are found to be significant. The findings show that higher organizational readiness strengthens the connection between AIR, ASDI, UDL and TRME, as all interaction terms are statistically significant. The obtained outcomes confirm that there is moderation in the model.

Additionally, the table shows that SIE works as a mediating factor. All indirect effects from AIR to TRME through SIE ($p = 0.00035$), ASDI to TRME through SIE ($p = 0.00032$) and UDL to TRME through SIE ($p = 0.00024$) are significant. The result shows that enhanced integration of systems is one way in which AIR, ASDI and UDL influence TRME.

Table 7: Path Analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIR -> SIE	0.421	0.422	0.033	12.830	0.000
AIR -> TRME	0.092	0.093	0.043	2.123	0.034
ASDI -> SIE	0.320	0.320	0.036	8.969	0.000
ASDI -> TRME	0.097	0.098	0.041	2.361	0.018
OCR -> TRME	0.169	0.171	0.045	3.736	0.000
SIE -> TRME	0.354	0.352	0.054	6.495	0.000
UDL -> SIE	0.413	0.413	0.035	11.899	0.000
UDL -> TRME	0.092	0.093	0.044	2.069	0.039
OCR x ASDI -> TRME	0.198	0.197	0.033	5.931	0.000
OCR x AIR -> TRME	0.208	0.206	0.037	5.562	0.000
OCR x UDL -> TRME	0.173	0.171	0.037	4.712	0.000
AIR -> SIE -> TRME	0.149	0.149	0.026	5.747	0.000
ASDI -> SIE -> TRME	0.113	0.113	0.022	5.073	0.000
UDL -> SIE -> TRME	0.146	0.146	0.026	5.624	0.000

4.5 Structural Model

As explained in Figure 3, the highlighted model demonstrates the relationships between main constructs and their statistical importance evaluated with t-values. The lines in the model are all marked with t-statistics and values above 1.96 signify that the results are statistically significant at the 5% level.

There is a clearly strong and relevant relationship between AIR and SIE, having a t-value of 12.830. It means that, on average, institutions that invest in AI technology manage to use smart systems more effectively. The changeover from Administrative Support for Digital Innovation (ASDI) to SIE indicates that leadership support is essential for system integration. The extra t-value in UDL of 11.899 means digital competence helps increase system effectiveness.

The effect of system integration on a training organization is statistically significant and strongly suggests better management efficiency. It shows that connecting systems helps training rooms be used more efficiently and their schedules improve. In addition, AIR, ASDI and UDL all show direct effects on TRME that are statistically significant: t-values of 2.123, 2.361 and 2.069 respectively. Even though these results are not big, they point out that a mix of infrastructure, support and user ability enhances efficiency besides the influence of integration.

It also factors in interaction effects to look at how OCR, i.e. Organizational Change Readiness, moderates the connection between the two main factors. All three predictors—AIR, ASDI and UDL—show significant interactions with OCR when looking at

TRME. The t-values of the interaction between OCR and AIR are 5.562, between OCR and ASDI are 5.931 and between OCR and UDL are 4.712. The research shows that better change readiness in institutions leads to a bigger positive contribution from infrastructure, support and digital knowledge to effective training sessions. This means OCR gives a bigger boost to these relationships, so it is an important factor for why AI is successful in any organization.

The correlation between AIR, ASDI and UDL and SIE is strong since they explain more than 42.7% of the difference among system integrations. The model, including interaction effects, explains 44.6% of the changes in training room efficiency. Relying on these values, we find that the model clearly explains what is happening.

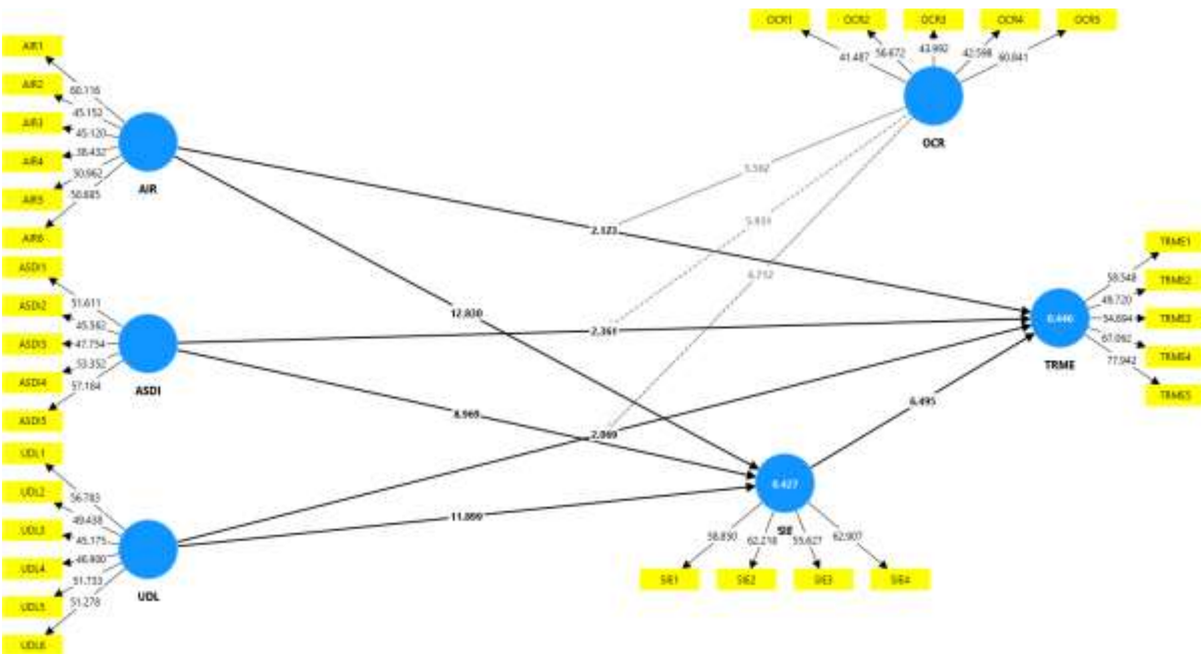

Figure 3: Structural Model

5. Discussion

The proposed model of intelligent training room management in higher vocational colleges is supported by the solid results found in this study. By considering infrastructure, organizational, user and change readiness together, the findings illustrate the many dimensions involved in changing schools with AI. All the paths tested—both direct, mediating and moderating—had statistical significance which confirmed the knowledge found in the existing literature.

An important finding is that AIR has a major influence on how effective system integration is. The purpose is similar to Sayari (2025) and Koukaras et al. (2025)'s point that AI solutions depend on having reliable foundational technology. Any institution with ready access to hardware, network infrastructure and the right devices is more likely to successfully add intelligent systems that manage schedules, track equipment and conserve resources. In the same way, both immediate and indirect connections between AIR and the efficiency of Training Room Management Efficiency (TRME) support that infrastructure is a basic requirement for system performance.

Administrative Support for Digital Innovation (ASDI) turned out to play a key role in shaping SIE and TRME. Such findings agree with those made by Galanti and Fantinelli (2024) and Aldous and Ismail (2025), who argue that a leader's endorsement and policy match are necessary for adopting technological innovations. Efficient administrative assistance supports the use of resources, spreads news about change and promotes long-term planning for AI to be used successfully. Both strategic planning and system enhancement play a role in how administrators influence the results of government.

Nikou et al. (2022) and MANHA et al. (2024) found that user digital literacy (UDL) greatly affected SIE and TRME and this study supports that finding. Such studies emphasize that for an education system to be usable and encourage users, everyone needs to be digitally competent. Enhanced digital skills mediated by SIE in the UDL–TRME relationship reveal that users are able to more effectively deal with integrated systems, leading to better outcomes in system management.

The research discovered that SIE is a crucial mediating factor affecting how effectively the system operates. In 2010, Shen et al. (2010) and in 2017, Glover et al. (2017) wrote that integration effectiveness is based on how well subsystems communicate, if interfaces are user-friendly and if digital platforms can work together. The current research adds to this view by confirming that SIE is shaped by both technical factors and people working in training rooms and this increase effectiveness in training rooms by improving scheduling, equipments used and energy management.

The addition of Organizational Change Readiness (OCR) to the model improves the analysis by being a direct predictor and a moderator. As these authors agree, change readiness means teams share certain attitudes that support changes in the organization. In this analysis, OCR led to better TRME and also improved how AIR, ASDI, UDL and TRME are related. This implies that when a culture and system are ready, newly created technology and strategies will work better than otherwise.

6. Conclusion

The purpose of this study was to build and prove experimentally an intelligent management system for training rooms in higher vocational colleges, powered by artificial intelligence. Using SmartPLS, the study was able to confirm the theoretical assumptions and show strong evidence that each hypothesis holds for the relationships between AI-Based Infrastructure Readiness (AIR), Administrative Support for Digital Innovation (ASDI), User Digital Literacy (UDL), System Integration Effectiveness (SIE), Organizational Change Readiness (OCR) and Training Room Management Efficiency (TRME).

It's clear from the results that the ability to integrate an information system depends on infrastructure, leadership and user involvement. As a result, SIE greatly improves how the training room is managed. In addition, the moderation results demonstrate that when organizations are ready for change, infrastructure, support and digital knowledge have a stronger impact on TRME. It becomes obvious that every step of digital transformation in schools should consider technology as well as the needs of employees and the organization as a whole.

Because it addresses a crucial disconnect in the literature, the study helps educational technology, AI management and smart campus development. It allows other learning institutions to use its structure when setting up intelligent facility management systems.

Policy Implications

The research offers useful advice to policy influencers in putting AI into practice in vocational schools. Ensuring core digital systems are built must be done first before AI can be applied. In addition, policies must highlight leading by example, setting aside funds, planning training and encouraging those who perform well to use digital services. Additionally, user digital literacy should be included in future development plans at every institution so that all staff and faculty can work with AI. Third, organizations should build a system that promotes readiness to change by working on communication strategies, involving stakeholders and running programs that promote flexibility. It is important to see AI adoption as integrated with other changes and strategies that support the country's main education and development goals.

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