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HYBRID SEM-ANN ANALYSIS OF AUGMENTED REALITY ADOPTION FOR HOSPITALITY TRAINING: EVIDENCE FROM AN EMERGING ECONOMY

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Abstract. This study investigates the adoption of augmented reality (AR) as a training tool for housekeeping staff in star-classified hotels in India, an emerging economy. Building on the Technological-Organisational-Environment (T-O-E) framework, this study extends the theory by exploring the interplay of behavioural antecedents influencing AR adoption under conditions of cost sensitivity and economic constraint. Using a hybrid SEM–ANN modelling approach with data from 300 hoteliers, the study identifies external support systems, organisational flexibility, and perceived competitive advantage as key facilitators of adoption, while cost perceptions and technological anxiety act as inhibitors. Crucially, technological self-efficacy is introduced as a moderating factor, strengthening the influence of technological environments on adoption intention. From an economic perspective, the results highlight how AR can reduce training costs, improve efficiency, and enhance competitiveness in low-margin service industries. In practice, the study recommends that hotels invest in "train-the-trainer" programmes to build managerial self-efficacy, thereby mitigating technological anxiety and promoting sustainable digital transformation. The research offers novel insights by applying a hybrid inference model to AR adoption in the hospitality sector, demonstrating its theoretical and practical relevance in emerging economies. Future research should expand the analysis to include more regions and test experimental interventions to validate causal relationships.

Keywords: technology adoption, economic cost, workforce development, T-O-E theory, emerging economy.

JEL Classification: O33, O31, M15, D83.

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1. Introduction

The hospitality industry's growing emphasis on service excellence and operational efficiency has heightened the importance of innovative training methodologies, particularly in emerging economies like India. The COVID-19 pandemic disrupted various sectors, from financial markets (Bannigidadmath et al., 2022), to hospitality (Rhama, 2022), where it heightened the need for innovative training solutions. As the sector evolves, traditional training approaches are supplemented with technological interventions to enhance service quality and maintain stringent cleanliness standards. Among these innovations, Augmented Reality (AR) has emerged as a transformative tool for employee training, offering immersive and interactive learning experiences (Domgue et al., 2025). Housekeeping staff are responsible for maintaining critical guest contact areas, from public spaces to complex HVAC (Heating, Ventilation, and Air Conditioning) systems, making their training fundamental to service quality. However, conventional training methods often fail to effectively demonstrate complex cleaning protocols and standard operating procedures. This challenge is particularly pronounced in emerging economies, where the hospitality sector faces rapid expansion and high employee turnover (Kumar et al., 2024). Integrating AR technology presents an opportunity to bridge this training gap by providing realistic, hands-on learning experiences that do not disrupt regular hotel operations. Currently, AR is being integrated into hospitality sectors like, events education and design (Ju et al., 2025), guest management (Jalilvand & Ghasemi, 2026), and hospitality marketing (tom Dieck et al., 2024). Furthermore, Lim et al. (2024) espouse that hotels that deploy AR mediated guest management applications experience a significant impact on the intention to stay and return.

Despite growing interest in AR applications, empirical evidence regarding its effectiveness in hospitality training remains limited, particularly in emerging economies. Since the advancement of the information science (IS) literature, significant scientific endeavours have been undertaken to understand the interaction between novel technologies and human propensities. A crucial advancement occurred in the mid-2000s when researchers began recognising the limitations of viewing technology adoption as a binary decision. This led to the emergence of process-oriented perspectives that examined adoption as a multi-stage phenomenon, incorporating pre-adoption, adoption, and post-adoption behaviours. A notable trend in recent years has been the integration of psychological constructs, such as technology self-efficacy, anxiety, and resilience, into adoption frameworks. This reflects a growing recognition that successful technology adoption requires an understanding of both technical and human factors, particularly in service-intensive industries such as hospitality (Han et al., 2024). Technological Self-Efficacy (TSE) refers to an individual's confidence in their ability to perform tasks using technology effectively. This construct is rooted in Bandura (1977), Hill et al. (1987) concept of self-efficacy, which pertains to confidence in executing actions required to manage prospective situations. In the context of AR adoption for training purposes, TSE becomes a critical factor, as employees with higher technological self-efficacy are more likely to engage with and effectively utilise AR-based training modules. Conversely, low TSE can lead to resistance, hindering the adoption process and diminishing the potential benefits of AR integration (Holden & Rada, 2014).

Despite India's emergence as a global IT hub and the rapid digital transformation of its hospitality sector, a critical research gap remains in understanding how emerging technologies, such as AR, can be effectively adopted for staff training, particularly in its unique socio-economic landscape (Goswami & Daultani, 2021). Vinodan and Meera (2025) reveal that while existing literature has explored technology adoption in developed markets, the distinct characteristics of India's hospitality sector, characterised by a mix of international chains and indigenous operators, hierarchical organisational structures, and varying levels of technological readiness, demand a more nuanced investigation. The T-O-E or Technology-Organisation-Environment framework, promulgated by Tornatzky and Fletscher (1990) offers a promising lens to examine these complexities. Yet, its application in emerging economy contexts, particularly for AR adoption in hospitality training, remains understudied.

This research gap becomes more significant considering India's labour market dynamics, where the availability of a skilled workforce often challenges the hospitality sector, making technology-enabled training solutions increasingly relevant (Jayawardena et al., 2023). Furthermore, integrating TSE into the T-O-E framework addresses the limitation of overlooking individual-level factors in organisational technology adoption studies. A more holistic understanding of the adoption process can be achieved by considering TSE within the technological context of the T-O-E framework. This integration acknowledges that the successful adoption of AR technology in hospitality training is not solely dependent on organisational readiness or external environmental factors, but is also significantly influenced by the technological confidence and competence of the individuals expected to use it.

Using a hybrid inference system and anchoring on the T-O-E model (Figure 1), the main aim of this investigation is to incorporate certain human factors to estimate the drivers and constrictors of adoption intention and extend the predictive capacity of the Technology-Environment-Organisation framework in the context of Indian hotels. According to the provisions and arguments provided above, the current study aims to investigate the following research questions:

RQ 1: What are the inhibitors and enablers of AR adoption intention among hotel housekeeping executives?

RQ 2: How does Technology Self-Efficacy's moderating role on the Technological Dimension of the Technology-Organisation-Environment framework predict AR adoption intention?

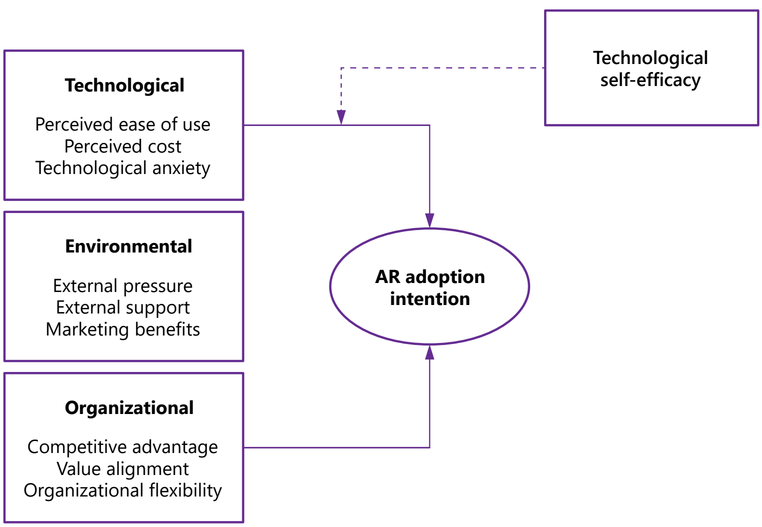

Figure 1. Theoretical framework (source: authors' own work)

2. Theory: a techno-economic T-O-E perspective

Propounded by Tornatzky and Fleischer (1990), the Technology–Organisation–Environment (T-O-E) framework provides a systemic lens for explaining innovation adoption by integrating technological, organisational, and environmental determinants. Unlike techno-centric models such as the Technology Adoption Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT), T-O-E embeds both human and non-human actors, making it especially suitable for emerging technologies like augmented reality (AR) (Awa & Ojiabo, 2016). Yet, prior applications of T-O-E often overlook the economic conditions shaping adoption, particularly in emerging economies where resource scarcity, institutional voids, and competitive pressures are more pronounced (Stojcic et al., 2025).

From a technological standpoint, AR enhances knowledge retention and training safety but raises cost and complexity concerns. In resource-constrained settings, such costs are significant. However, adoption economics suggest that high cost may signal quality and competitive seriousness, motivating adoption rather than deterring it (Manasseh et al., 2023). Similarly, technological anxiety may trigger proactive investment to avoid obsolescence. This study incorporates technological self-efficacy to capture how managerial confidence reframes these cost–benefit calculations.

The organisational dimension emphasises structural flexibility, managerial commitment, and absorptive capacity. Firms with greater digital maturity are more likely to leverage AR for workforce development (Tussyadiah et al., 2018). Consistent with evidence on firm heterogeneity among emerging economies, such firms translate innovation into competitive advantage (Su et al., 2026). The environmental dimension reflects regulatory mandates, vendor ecosystems, and competitive pressures. For example, post-COVID hygiene requirements act as regulatory shocks that accelerate digital adoption (Su et al., 2025). Meanwhile, institutional weaknesses elevate transaction costs, though spillovers from global hotel chains can offset information asymmetries (Akbar & Tracogna, 2022).

The above dimensions extend T-O-E into a techno-economic perspective, highlighting how AR adoption in emerging economies is not merely a technological decision but a strategic economic response to constraints and opportunities that shape long-term competitiveness.

3. Literature review

The adoption of emerging technologies has been widely examined across information systems and innovation economics, particularly to understand how firms respond to technological change under conditions of uncertainty and resource constraint. In emerging economies, technology adoption decisions are shaped not only by technical feasibility but also by institutional, economic, and organisational limitations. The Technology–Organisation–Environment (TOE) framework has been frequently employed to explain such decisions because it captures both internal and external determinants of adoption. However, existing studies often apply TOE in a fragmented manner, focusing on isolated variables rather than examining broader structural and behavioural gaps, especially in service-intensive sectors such as hospitality.

Within the technological dimension, perceived ease of use, perceived cost, and technology-related anxiety have been extensively discussed as antecedents of adoption (Davis, 1989). Prior research suggests that ease of use lowers cognitive effort and encourages experimentation with new technologies, particularly in contexts where digital literacy varies significantly (He et al., 2018; Venkatesh, 2000). However, studies also indicate that ease of use does not operate uniformly across cultures and sectors, and its relevance may differ in emerging economies where managerial experience and exposure to advanced technologies remain uneven (Che Nawi et al., 2022). This creates a knowledge gap regarding how usability perceptions interact with economic constraints in service industries

Another aspect of the TOE framework, perceived cost, remains one of the most debated factors in technology adoption research. While cost sensitivity is commonly reported as a barrier in developing economies, recent studies argue that cost perceptions may act as a strategic filter rather than a pure deterrent (Pantano et al., 2017). In low-margin industries, managers often weigh long-term efficiency gains against short-term financial pressure, suggesting a more complex cost-adoption relationship than previously assumed (Ashrafi, 2023; Ahmad & Scott, 2019; Haans et al., 2016). Similarly, technology anxiety has traditionally been viewed as a psychological inhibitor; however, most existing research focuses on conventional information systems rather than immersive technologies, such as augmented reality (Nhan Vo et al., 2022). Strengers and Nicholls (2017), through their study pertaining to technology diffusion among emerging countries, reveal a practical gap in understanding how anxiety manifests when technologies are perceived as inevitable for competitive survival.

The organisational dimension of TOE emphasises internal readiness, flexibility, and strategic orientation. Research consistently shows that organisations with adaptive structures and digitally mature leadership are better positioned to integrate new technologies (Gangwar et al., 2014). In emerging economies, however, organisational flexibility is often constrained by rigid hierarchies, limited training investment, and short-term performance pressures (Shamburg, 2004). Despite its relevance, organisational flexibility is frequently examined as an outcome of adoption rather than a precondition, particularly in hospitality research (Holden & Rada, 2014).

Competitive advantage and perceived benefits represent strategic motivations for adoption. Prior studies confirm that firms adopt technologies not only to improve efficiency but also to signal innovation capability and service quality (Lee & Yang, 2013; Sheel & Nath, 2019; Varukolu & Park-Poaps, 2009). Nevertheless, empirical evidence from emerging economies remains limited, especially regarding how service firms perceive competitive advantage in relation to employee training technologies. This highlights a gap in understanding how intangible benefits and strategic positioning influence adoption decisions beyond operational advantages.

Another integral component of the TOE, value alignment has received comparatively little attention in TOE-based studies, despite its importance in organisational decision-making (Tallon, 2014). Existing literature suggests that firms are more inclined to adopt technologies that resonate with their cultural norms and managerial values (Yang & Lee, 2019). However, research on value alignment in emerging economy service sectors remains scarce, leaving unanswered questions about how cultural compatibility shapes technology acceptance at the organisational level.

The environmental dimension captures regulatory forces, competitive pressure, and external support. Studies in emerging economies emphasise that external pressure often accelerates adoption by creating mimetic behaviour among firms facing intense competition (Awa & Ojiabo, 2016). Regulatory mandates related to health, safety, and digital compliance further amplify this pressure (Paydar et al., 2014). At the same time, external support from vendors and industry networks plays a critical role in reducing uncertainty and knowledge gaps (Manrai & Gupta, 2020). Yet, empirical findings remain inconsistent, with some studies reporting a limited influence of external support due to institutional inefficiencies and fragmented ecosystems. This highlights the need for a deeper investigation into how environmental forces interact with organisational and technological factors in emerging markets.

Recent studies indicate that conceptualising the technological context solely as a composite of perceived ease of use, cost, and anxiety provides an incomplete explanation of technology adoption behaviour in emerging economies (Gangwar et al., 2014). Evidence from development and productivity economics shows that the economic returns from digital technologies depend not only on access but also on managerial capability and confidence in technology use (Cirera et al., 2022). When technological self-efficacy is low, firms struggle to translate favourable technological conditions into effective adoption, resulting in underutilisation and delayed diffusion. Conversely, high self-efficacy enhances managers' ability to overcome cost concerns and psychological resistance, strengthening the influence of the technological environment on adoption intention. This positions technological self-efficacy as a critical moderating antecedent that explains heterogeneous adoption outcomes under similar technological and economic constraints, particularly in service-oriented sectors in emerging markets.

The above antecedents, which are derived from the theoretical positions of the TOE framework provide for the installations of the following postulations:

H1: *Perceived ease of use has a positive influence on managerial intention to adopt augmented reality.*

H2: *Perceived cost negatively influences managerial intention to adopt augmented reality.*

H3: *Technology anxiety negatively influences managerial intention to adopt augmented reality.*

H4: *External support from vendors, industry networks, and stakeholders has a positive influence on managerial intention to adopt augmented reality.*

H5: *External pressure arising from competitive and regulatory forces has a positive influence on managerial intention to adopt augmented reality.*

H6: *Perceived benefits associated with augmented reality adoption positively influence managerial intention to adopt augmented reality.*

H7: *Perceived competitive advantage positively influences managerial intention to adopt augmented reality.*

H8: *Value alignment between organisational culture and augmented reality technology has a positive influence on managerial intention to adopt augmented reality.*

H9: *Organisational flexibility positively influences managerial intention to adopt augmented reality.*

H10: *echnological self-efficacy positively moderates the relationship between the technological environment and managerial intention to adopt augmented reality, such that the relationship becomes stronger at higher levels of technological self-efficacy.*

4. Research methodology

4.1. Research design and sample

This study employed a cross-sectional survey design to investigate the factors influencing the adoption of Augmented Reality (AR) technologies among managerial staff in the Indian hospitality sector. The target population comprised C-Suite, middle and lower managerial positions—housekeeping, human resource, training, and general managers—across various hotel classifications.

To recruit participants, a non-probability snowball sampling technique was utilised. Initial participants were identified through the researchers' professional and academic networks within the hospitality industry. These initial contacts were then asked to refer additional eligible participants within their professional circles. This referral process continued iteratively until the desired sample size was achieved. Snowball sampling is particularly effective in accessing specific professional groups and is well-suited for studies where a comprehensive sampling frame is unavailable (Rodríguez Sánchez et al., 2022). The sampling process yielded participation from 300 individuals across 50 hotels in India, including 10 5-star, 20 4-star, and 20 3-star establishments. This approach ensured a diverse representation of hotel classifications and geographic locations.

Prior to data collection, a power analysis was conducted using G*Power (version 3.1.9.7) to determine the minimum required sample size to detect a medium effect size ($f^2 = 0.15$) with a power of 0.80 and an alpha level of 0.05. The analysis indicated a minimum sample size of 150 participants. To enhance the robustness of the findings and mitigate potential biases and under-sampling issues associated with non-probability sampling methods, the sample size was doubled to 300 participants. The survey instrument underwent a rigorous pre-testing phase involving 20 respondents and six scholars specialising in hospitality management from the UK, India, Malaysia, and France. This pre-testing aimed to ensure the clarity, relevance, and cultural appropriateness of the questionnaire items. Refer to Table 1 for details on survey administration, and to Table 2 for descriptive demographic information about the participants.

Table 1. Survey campaign details (source: authors' own work, 2025)

Time Slice	Period	Parts of Survey Filled	Total Number of Surveys Shared	Surveys Filled and Eligible	Response Rate
1	April 2022	Demography Inquiries and Technological aspect of T-O-E	300	275	91.66%
2	June 2022	Organisational and Environmental Aspects of T-O-E	275	260	94.54%
3	August 2022	Technological Self-Efficacy and AR Adoption Intention	260	250	96.15%

Table 2. Demographic details (source: authors 'own work, 2025)

Demographic Variable	Category	Number of Respondents	Percentage (%)
Gender	Female	120	40%
	Male	180	60%
Marital Status	Married	210	70%
	Single	90	30%
Age Group	25–34 years	75	25%
	35–44 years	90	30%
	45–54 years	90	30%
	55–65 years	45	15%
Highest Education Level	Tertiary (Diploma)	60	20%
	Bachelor's Degree	90	30%
	Master's Degree	150	50%
Annual Income (INR)	₹500,000 – ₹624,999 (approx. €5,555 – €6,944)	75	25%
	₹625,000 – ₹749,999 (approx. €6,944 – €8,333)	90	30%
	₹750,000 – ₹874,999 (approx. €8,333 – €9,722)	90	30%
	₹875,000 – ₹1,000,000 (approx. €9,722 – €11,111)	45	15%
Size of Hotel Corporation	Small-Mid	60	20%
	Mid-Large	90	30%
	Large-Chain	150	50%
Designation	C-Suite (Promoter, VP, MD, Board of Governors Representative)	150	50%
	Mid-Level Management (Controllers, Managers, Head of Department)	120	40%
	Lower-Level Management (Supervisors, Executives)	30	10%

4.2. Measurement items

The psychometric questionnaire housed 46 items forming 11 constructs. A seven-point Likert scale was deployed to capture the responses. The construct known as the Intention to Adopt AR Technology (ITA) was adopted by Davis (1989) and had five items. Another variable in the model, Perceived ease of use (PEU), was adopted from Henao-Ramírez and López-Zapata (2022) , it constituted four items. Technology Anxiety (TAX) was derived from Morosan (2021) and comprises six items. Two constructs, Perceived Cost (PEC) and Perceived Behavior (PEB), both espoused by Ngah et al. (2022) consisted of four and five items, respectively.

Six items used to measure External Pressure (EXP) were developed following the guidelines of Pearson and Grandon (2005). External Support (EXS) was measured by four items refined from Chatterjee et al. (2021). Three items modified from Sheel and Nath (2019) composed

Competitive Advantage (CAD) in the model. Three items, each gauged Value Alignment (VAN) and Organisational Flexibility (OFX), were adopted from Karahanna et al. (2006). The moderating operator, Technological Self-Efficacy (TSE), was adopted from Brinkerhoff (2014). The final instrument is given in Table 3.

Table 3. Survey instrument (source: authors' own work, 2025)

Construct	Item	References
Intention to Adopt AR Technology (ITA)	ITA1: I intend to use AR technology for training in the near future. ITA2: I will recommend the use of AR for training housekeeping staff. ITA3: I plan to increase my use of AR technology in staff training. ITA4: Using AR for training would be a good idea. ITA5: I am likely to adopt AR-based training in my department.	Davis (1989)
2. Perceived Ease of Use (PEU)	PEU1: Learning to operate AR technology would be easy for me. PEU2: I believe that interacting with AR systems would be clear and understandable. PEU3: It would be easy for me to become skillful at using AR technology. PEU4: I would find AR technology easy to use in training contexts.	Henao-Ramírez and López-Zapata (2022)
3. Technology Anxiety (TAX)	TAX1: I feel apprehensive about using AR technology. TAX2: I get nervous when I think about using AR for training. TAX3: I fear I might make mistakes using AR systems. TAX4: The idea of using AR makes me uncomfortable. TAX5: I feel hesitant to rely on AR for training purposes. TAX6: I worry that I may not understand how to use AR effectively.	Morosan (2021)
4. Perceived Cost (PEC)	PEC1: Implementing AR training programs would be expensive. PEC2: The costs of using AR technology outweigh the benefits. PEC3: Budget constraints are a major barrier to adopting AR. PEC4: AR training programs require significant financial investment.	Ngah et al. (2022)
5. Perceived Behavior (PEB)	PEB1: I tend to use technology if I believe it adds value. PEB2: My intention to use AR depends on my personal comfort with technology. PEB3: I consider how technology fits into my daily tasks before using it. PEB4: I usually rely on proven technology before trying something new. PEB5: My habits and attitudes shape how I adopt new technologies.	Ngah et al. (2022)
6. External Pressure (EXP)	EXP1: Industry trends influence our decision to use AR. EXP2: Competitor actions affect our interest in AR technology. EXP3: There is pressure from upper management to adopt innovative training tools. EXP4: Government regulations encourage us to digitise training. EXP5: Customer expectations push us toward technology adoption. EXP6: We feel the need to stay ahead of competitors by using new technology.	Pearson and Grandon (2005)

End of Table 3

Construct	Item	References
7. External Support (EXS)	EXS1: We have access to technical support for implementing AR. EXS2: Technology providers offer good after-sales support for AR solutions. EXS3: We can access training resources for learning AR. EXS4: External consultants or vendors are available to help with AR deployment.	Chatterjee et al. (2023)
8. Competitive Advantage (CAD)	CAD1: Using AR in training would give our hotel a competitive edge. CAD2: AR adoption can help differentiate us from other hotels. CAD3: AR will improve the quality of service offered by our staff.	Sheel and Nath (2019)
9. Value Alignment (VAN)	VAN1: The use of AR aligns with our organisation's values. VAN2: AR adoption fits with our long-term training goals. VAN3: There is a good match between AR technology and our organisational vision.	Karahanna et al. (2006)
10. Organisational Flexibility (OFX)	OFX1: Our organisation is quick to adapt to new technologies. OFX2: We encourage experimentation with innovative tools like AR. OFX3: Our hotel structure supports the adoption of new training methods.	Karahanna et al. (2006)
11. Technological Self-Efficacy (TSE) (Moderator)	TSE1: I am confident in my ability to use AR technology. TSE2: I believe I can troubleshoot basic issues with AR systems. TSE3: I feel capable of learning new technological tools. TSE4: I can teach others how to use AR for training purposes.	Brinkerhoff (2014)

4.3. Analysis of data

This study employed a hybrid analytical approach, integrating Partial Least Squares Structural Equation Modelling (PLS-SEM) and Artificial Neural Networks (ANN), to investigate the predictors of augmented reality (AR) adoption intention among Indian hoteliers. The dependent variable, intention to adopt AR, was measured continuously, capturing varying degrees of adoption propensity. PLS-SEM was chosen for its ability to handle complex models with multiple constructs and indicators, particularly when the primary objective is prediction and theory development. This method is advantageous in exploratory research scenarios where the model includes numerous latent variables and indicators (Sternad Zabukovšek et al., 2022). Additionally, PLS-SEM is robust to deviations from normality and is suitable for small to medium sample sizes, making it appropriate for this study's context. While logistic regression models, such as logit and probit, are typically employed for binary dependent variables, the continuous nature of the dependent variable in this study rendered PLS-SEM a more fitting choice. ANN was incorporated to capture complex, non-linear relationships among variables often present in technology adoption behaviours. Neural networks are adept at modelling intricate patterns within data, providing a dense understanding of the factors influencing AR adoption. While alternative machine learning techniques, such as Random Forests and decision trees, are valuable, ANN has demonstrated superior performance in capturing non-linear patterns in certain scenarios (Ahmad et al., 2017). The integration of PLS-SEM and ANN leverages the strengths of both methods, offering a comprehensive analytical framework that captures both linear and non-linear relationships (Foo et al., 2018; Singh et al., 2009).

4.4. Structural model analysis

The researchers conducted checks to assess the robustness of the measurement model. The observed factor loadings were all >0.7, and the Average Variance Extracted was recorded as greater than >0.50. The Cronbach's Alpha values and Composite reliability were >0.7, meeting the established criteria (Sarstedt et al., 2016). Table 4 provides the details of all readings.

Table 4. Convergence, reliability and multicollinearity (source: authors' own work, 2025)

Constructs	λ	AVE	Comp.Rel	Chronbach's α	σ_A	VIF
Competitive Advantage (CAD)	0.787 0.796 0.862	0.665	0.856	0.750	0.767	1.566
External Pressure (EXP)	0.843 0.864 0.839 0.870 0.854 0.845	0.727	0.941	0.925	0.925	2.041
External Support (EXS)	0.794 0.815 0.810 0.766	0.634	0.874	0.807	0.807	2.350
Intention to Adopt AR (ITA)	0.865 0.852 0.866 0.872 0.850	0.742	0.935	0.913	0.913	N/A
Perceived Benefits (PEB)	0.847 0.854 0.798 0.825	0.691	0.899	0.851	0.853	1.974
Organisational Flexibility (OFX)	0.856 0.824 0.831	0.701	0.876	0.787	0.790	2.040
Perceived Cost (PEC)	0.794 0.847 0.818 0.814	0.670	0.890	0.835	0.836	2.788
Technology Anxiety (TAX)	0.771 0.872 0.853 0.863 0.861 0.814	0.705	0.935	0.916	0.917	2.459
Value Alignment (VAN)	0.869 0.850 0.807	0.710	0.880	0.796	0.802	2.562
Perceived Ease of Use (PEU)	0.899 0.874 0.895 0.869	0.782	0.935	0.907	0.909	2.449
Technological Self-Efficacy (TSE)	0.862 0.866 0.884 0.859	0.754	0.924	0.8912	0.892	2.667

Heterotrait-Monotrait Ratio (HTMT) was used to gauge discriminant validity. Usually, HTMT values close to 1 indicate a lack of discriminant validity. Hair et al. (2017) suggest a conservative threshold of <0.85 (suggests that the constructs are sufficiently different). According to Table 5, the model appears to satisfy the criteria.

Table 5. Heterotrait-Monotrait Ratio (HTMT) (source: authors' own work, 2025)

Construct	ITA	TSE	PEU	TAX	PEC	EXS	EXP	PEB	VAN	OFX	CAD
ITA											
TSE	0.752										
PEU	0.719	0.505									
TAX	0.759	0.577	0.760								
PEC	0.812	0.654	0.763	0.699							
EXS	0.773	0.647	0.630	0.593	0.800						
EXP	0.692	0.581	0.587	0.556	0.671	0.709					
PEB	0.701	0.569	0.538	0.506	0.676	0.729	0.596				
VAN	0.847	0.726	0.678	0.761	0.831	0.755	0.715	0.738			
OFX	0.723	0.634	0.557	0.526	0.739	0.704	0.539	0.673	0.828		
CAD	0.640	0.5030	0.4046	0.5336	0.5524	0.6035	0.5590	0.570	0.684	0.483	

4.5. Measurement model analysis

In tandem with observations from Hair et al. (2017), effect size and path coefficients were used to test the hypotheses formulated. This study used 5,000 subsamples to test the bootstrapped model to identify significant relationships. The study used a 5% significance level to test the hypotheses, with p-values <0.05. Tables 6 and 7 present the direct relationships and interactive effects observed after bootstrapping. The results indicate that all nine pathways are significant at $p < 0.05$. The R^2 was estimated at 0.713, implying that the exogenous variables explain 71% of the variance in the endogenous variable in the model.

Table 6. Structural model (source: authors' own work, 2025)

Effect	β	Samp. $\bar{x}$	Std. ϵ	t-value	p-value	f^2	Empirical Remark
PEU -> ITA	0.114	0.107	0.046	2.460	0.0007	0.213	Accepted
TAX -> ITA	0.190	0.195	0.058	3.251	0.0006	0.180	Rejected
PEC -> ITA	0.104	0.101	0.045	2.672	0.0078	0.153	Rejected
EXS -> ITA	0.082	0.079	0.043	2.877	0.0042	0.213	Accepted
EXP -> ITA	0.079	0.079	0.040	2.944	0.0034	0.134	Accepted
PEB -> ITA	0.089	0.088	0.043	2.670	0.0078	0.153	Accepted
VAN -> ITA	0.079	0.082	0.047	2.683	0.0075	0.102	Accepted
OFX -> ITA	0.085	0.082	0.039	2.852	0.0045	0.154	Accepted
CAD -> ITA	0.090	0.093	0.040	2.639	0.0086	0.233	Accepted

Testing the moderation effect of technical self-efficacy

As discussed above, the study adopted a two-stage interaction-term analysis. First, it examined how the interaction term (TSE) performed as an independent variable in the structural model. From Table 6 above, the researchers conclude that TSE significantly measured AR adoption intention. Secondly, the three pillars of the Technological Environment, namely, PEU, PEC, and TAX, were merged into one latent factor named Technological Environment (TEC) using a two-stage approach in tandem with Sarstedt et al. (2019). The moderation analysis followed. Table 5 below shows that the study observed a significant moderating relationship (β = 0.679, t-value = 12.338) between TEC and TSE in predicting AR adoption intention.

Table 7. Interaction effect (source: authors' own work, 2025)

Effect	β	Samp. x̄	Std. ϵ	t-value	p-value (1-sided)	f^2	Remark
TEC*TSE -> ITA	0.679	0.679	0.055	12.333	0.0000	0.246	Accepted

4.6. Neural model analysis

The study used a hybrid modelling technique combining Structural Equation Modelling and Artificial Neural Networks to determine the key determinants of AR adoption intention. The ANN modelling was performed in RStudio and IBM SPSS v22. The study used a Sigmoid-activated Multilayer Perceptron (MLP), with 90% of the data for training and 10% for testing. The deep neural network used in this study has 10 nodes in the first hidden layer and 5 in the second.

Following the recommendations of Foo et al. (2018), the researchers conducted a 10-fold cross-validation to assess robustness and model fit. According to Tiwari and Young Chong (2020), the metrics to gauge the prediction accuracy of the ANN model are the standard deviation (Õ) and mean (x̄) of the Root Mean Squared Error (RMSE). The former has further expedited that the lower the RMSE, the better the model's fit. From Table 8, the researchers

Table 8. RMSE values (source: authors' own work, 2025)

Network Cross-Validation	Training Set (Intention to Adopt)		Testing Set (Intention to Adopt)	
	SSE	RMSE	SSE	RMSE
1	34.912	0.399	4.466	0.386
2	44.923	0.448	7.982	0.565
3	44.837	0.450	5.801	0.455
4	58.177	0.508	2.841	0.344
5	48.87	0.470	2.823	0.318
6	34.447	0.393	4.078	0.396
7	51.561	0.481	4.989	0.438
8	35.83	0.406	3.178	0.315
9	37.596	0.412	7.292	0.520
10	42.129	0.446	7.043	0.436
X̄	43.328	0.441	5.049	0.417
Õ	7.916400737	0.038395714	1.90882128	0.082823018

observe that the mean RMSEs for both the training set (TNG) and the testing set (TST) are relatively low ($\bar{X}_{TNG}$ = 0.417 & $\bar{X}_{TST}$ = 0.441). Similarly, the standard deviation of the RMSE across both datasets is also low ($\tilde{O}_{TNG}$ = 0.38 & $\tilde{O}_{TST}$ = 0.82). The researchers confirm the ANN model's robust predictive capacity based on the results of this analysis.

After confirming the ANN model's robust predictive capacity, the researchers conducted a sensitivity analysis (Ref. Table 9) to uncover latent patterns in the data. They interpret that while the moderating variable of Technological Self-Efficacy has the highest involvement in determining adoption intention, technological anxiety is the least important. This finding provides empirical support for TSE's candidacy as a competent moderator in understanding the enablers of AR adoption.

Table 9. Sensitivity analysis (source: authors' own work, 2025)

Normalised Score												NRS	Ranking
Variable	NN1	NN2	NN3	NN4	NN5	NN6	NN7	NN8	NN9	NN10	Mean		
TSE	1.00	0.42	0.7	0.31	1.00	0.73	0.85	0.70	0.45	0.53	0.67	100%	1.00
PEU	0.32	0.22	0.41	0.25	0.36	0.29	0.49	0.32	0.33	0.12	0.311	47%	7.00
OFX	0.72	1.00	0.65	0.56	0.68	0.85	0.78	0.45	0.35	0.35	0.639	96%	2.00
PEC	0.39	0.26	0.1	0.33	0.22	0.33	0.21	0.61	0.38	0.26	0.309	46%	9.00
EXS	0.47	0.46	0.35	0.85	0.15	0.58	0.36	0.41	0.53	0.26	0.442	66%	4.00
EXP	0.48	0.26	0.17	0.76	0.46	0.52	0.21	0.4	0.35	0.19	0.38	57%	6.00
PEB	0.4	0.15	0.12	0.37	0.08	0.55	0.19	0.33	0.26	0.19	0.264	40%	8.00
VAN	0.63	0.39	0.38	0.58	0.77	0.44	0.47	0.32	0.39	0.30	0.467	70%	3.00
TAX	0.42	0.17	0.1	0.59	0.26	0.27	0.19	0.2	0.15	0.15	0.25	37%	10.00
CAD	0.63	0.37	0.18	0.49	0.13	0.41	0.28	0.87	0.42	0.3	0.408	61%	5.00

Note: NN (Neural Network); NRS (Normalised Score).

5. Results and discussion

The first hypothetical pathway was to study the correlation between Perceived Ease of Use and AR adoption intention. The PLS-SEM output indicated that the relationship was significant (β = 0.1144, t-value = 2.4600, $p < 0.05$). This finding resonates with Chatterjee et al. (2021), who documented a positive effect of the above variables among Indian manufacturing companies.

The second and third hypotheses, which predicted negative associations between TAX and PEC towards AR adoption intention, were found to be positively associated with the output of interest. Contrary to the hypothesised negative effects (Ahmad & Scott, 2019), both constructs showed significant positive associations with adoption intention. This suggests that, under certain conditions, what was presumed to be an inhibiting effect may be a trigger for compensatory behaviours, prompting managers to adopt AR to pursue greater efficiency. In a pioneering study about this particular organizational behaviour, Ahuja and Katila (2004) argue that constraint-induced stress can stimulate strategic experimentation and technology-enabled efficiency seeking, particularly in resource-constrained emerging economies.

The fourth hypothesis tested whether External Pressure (EXP) influences the intention to adopt AR. The results provide strong empirical support: Indian hotel managers clearly perceive competitive intensity as a catalyst for adopting digital training. Both large chains and smaller rivals exert pressure, prompting managers to set higher operational benchmarks and to turn to AR to sustain market relevance (Ukobitz & Faullant, 2022). This highlights that competition is not merely a background condition but a direct driver of proactive technology adoption in the hospitality sector.

The fifth hypothesis examined the role of External Support (EXS), including vendors, customers, and technology partners. The evidence confirms that supportive external ecosystems significantly strengthen AR adoption intentions. Managers in the current sample consistently pointed to the availability of vendor expertise, reliable customer backing, and collaborative partnerships as practical enablers in overcoming uncertainties about AR deployment. This indicates that adoption decisions are strongly shaped by the perceived reliability of external actors (Sivathanu, 2019), underscoring that AR diffusion in hospitality depends not only on organisational readiness but also on the vibrancy of the surrounding support network.

The sixth hypothesis, which examined the effect of Perceived Benefits (PEB) on AR adoption intention, was strongly supported. Results show that managers in Indian hotels are significantly more willing to adopt AR when they anticipate clear operational and service-related gains. This includes improved housekeeping efficiency, enhanced customer satisfaction, and reduced training time. The evidence highlights that adoption decisions are shaped less by abstract technological features and more by tangible performance outcomes. While earlier studies in India (Dubey & Sahu, 2021; Kannabiran, 2012; Manrai & Gupta, 2020) also emphasised perceived utility, this study provides direct evidence of PEB as a central driver of AR-based workforce training in hospitality, thereby extending prior findings to a new context.

The seventh hypothesis examined the role of Competitive Advantage (CAD), which was also positively supported. Managers demonstrated a clear orientation toward leveraging AR to differentiate themselves in an intensely competitive service market. Although CAD has not been extensively studied in India, the results resonate partially with Varukolu and Park-Poaps (2009), who observed that managers gravitate toward new technologies when they foresee reputational or strategic leverage. In the current study, CAD reflects the perception that AR adoption enables hotels to signal modernity, improve brand positioning, and secure a first-mover advantage in a recovering tourism economy.

The eight theoretical positions stated that Value Alignment positively affected AR adoption intention. This supposition is positively accepted. After thoroughly examining literature from leading scientific databases (Web of Science and Scopus), the authors did not find any investigations on 'value alignment' in the Indian context. This study shows that Augmented Reality and its adoption align with the corporate value systems of the Indian hoteliers surveyed. The examined housekeeping executives and managers perceive that adopting AR capabilities will align well with the hotel's existing corporate culture.

The authors tested the relationship between Organisational Flexibility and AR adoption intention through the ninth hypothesis. Results from the inferential statistics showed a positive association. Examinations conducted in the Indian setting by Dubey et al. (2019) treated OFX as an outcome of technological adoption, and none were representative of the hospitality segment. This study confirms that housekeeping executives and managers believe that adopting AR can enable their organisations to adapt to market dynamics and technological advancements.

Furthermore, findings provide robust evidence that Technological Self-Efficacy (TSE) significantly moderates the relationship between the technological environment and AR adoption intention. TSE, defined as an individual's confidence in handling technology-related tasks, amplifies the benefits of a supportive technological environment. Specifically, when TSE is high, advanced infrastructure and accessible resources translate into stronger adoption intentions; when TSE is low, even well-equipped environments risk underutilization. This observation highlights that technological readiness alone is insufficient; managerial belief in their capacity to use AR critically determines adoption outcomes. The result aligns with broader evidence on the moderating role: Xu et al. (2024) showed that Internet Self-Efficacy shaped e-government adoption, while Shata and Hartley (2025) confirmed its influence on cognitive and emotional responses to technology. By integrating this finding, the study underscores TSE as the most influential driver of AR adoption in hospitality, validating its central role in extending the TOE framework (Gangwar et al., 2015)

The ANN results confirmed Technological Self-Efficacy (TSE) as the most influential predictor of AR adoption, underscoring its economic importance in emerging markets. High TSE enables managers to fully exploit technological infrastructure, reducing underutilisation and maximising returns on investment. From an economic standpoint, self-efficacy lowers adoption transaction costs by mitigating uncertainty and behavioural resistance (Linh et al., 2026), thereby enhancing productivity gains from digital technologies. This complements evidence that managerial capability is a critical driver of firm-level technology adoption and productivity heterogeneity (Wang et al., 2026). Furthermore, organisational flexibility and value alignment ranked higher than TSE in importance, indicating that adaptive structures and cultural congruence help firms internalise innovation benefits. Conversely, cost and anxiety were least impactful once confidence was established, suggesting that capability investments outweigh barrier perceptions in shaping adoption behaviour in resource-constrained economies.

6. Conclusions

This study offers novel insights into the adoption of Augmented Reality (AR) in the hospitality sector by addressing a largely unexplored problem: the use of immersive technologies for manpower training in an emerging economy. The research advances theory and practice through three key scientific novelties. First, it introduces a hybrid SEM–ANN modelling approach to the Technological–Organisational–Environmental (T-O-E) framework, offering a multi-layered analytical method rarely applied in hospitality and technology adoption research. Second, it extends the T-O-E model by incorporating Technological Self-Efficacy (TSE) as a moderating variable, enriching its explanatory power and bridging behavioural and organisational perspectives. Third, the findings reveal counterintuitive results, such as the positive effects of perceived cost and technological anxiety—that challenge dominant theoretical assumptions and open avenues for international comparative research.

From an economic and financial standpoint, AR adoption can improve workforce productivity, enhance training efficiency, and strengthen competitive advantage, critical outcomes in low-margin industries such as hospitality. By reducing training costs, minimising service errors, and aligning with stricter post-pandemic hygiene regulations, AR contributes directly to the Sustainable Development Goals (SDGs) linked to innovation, decent work, and responsible consumption. These findings are relevant not only to India but also to other emerging economies, where digital capability-building is tied to long-term economic growth and resilience.

Practical recommendations flow naturally from these findings. Managers should prioritise investments in employee self-efficacy through structured "train-the-trainer" programmes that enable staff to overcome technological anxiety. Hotels must also continuously upgrade AR applications with intuitive design, advanced search tools, and personalised training modules to foster adoption and customer loyalty. Stakeholder support, whether from vendors, industry peers, or customers, is crucial for successful implementation, while organisational flexibility ensures adaptability in a competitive, regulation-driven environment. By positioning AR as a strategic enabler rather than a cost burden, hotels can enhance service quality, brand reputation, and long-term profitability.

The study's strengths lie in its integrated methodological design and focus on managerial perceptions, offering actionable insights for both scholars and practitioners. However, limitations include the modest sample size and the reliance on a single-country context, which may constrain generalisability. Future research should adopt cross-national comparisons, longitudinal designs, and multi-theory integration to deepen understanding of heterogeneity in AR adoption pathways.

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Author contributions

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