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Beyond Technology: A Multi-Theoretical Examination of Immersive Technology Adoption in Indian Healthcare

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Abstract:

Adopting immersive technologies in healthcare systems presents opportunities and challenges, particularly in emerging economies. Drawing on the Technology-Organization-Environment framework and Diffusion of Innovation theory, this research explores the key factors that drive the adoption of these technologies. Our findings reveal that organizational and environmental factors, including adaptability to change, regulatory support, and leadership commitment, have a stronger impact on facilitation adoption than technological aspects. These findings contribute to technology adoption theory by elucidating the contextual nature of facilitator importance in complex healthcare system settings. The study provides practical insights for healthcare administrators and policymakers on fostering an environment conducive to immersive technologies. It provides valuable implications for both theoretical development and practical application in healthcare technology management, particularly within emerging economies.

Keywords: Immersive Technology, Healthcare, Technology Adoption, Organizational Factors, Environmental Factors, Grey DEMATEL.

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1 Introduction

The healthcare system has witnessed unprecedented digital transformation, with information technology (IT) becoming increasingly central to healthcare delivery and patient care. Global digital health expenditure reached $288 billion in 2023 and is expected to grow to $1.5 trillion by 2030, reflecting the rapid adoption of digital solutions in the industry[1]. The digital revolution includes various technologies, from electronic health records and telemedicine to artificial intelligence and robotics, fundamentally reshaping how healthcare services are delivered and accessed (Tang et al., 2022; Chengoden et al., 2023). The remarkable progress in emerging technologies such as machine learning (ML), artificial intelligence (AI), blockchain, virtual reality (VR), and augmented reality (AR) has significantly impacted the healthcare sector and diversified methods of healthcare service delivery. These technological developments have improved access to healthcare services and remote treatment for patients (Tang et al., 2022). Additionally, the swift progression of digitization and automation has propelled growth in the healthcare sector, generating new opportunities and providing more affordable treatment choices (Bhuiyan et al., 2021). The COVID-19 pandemic has further accelerated this transformation, compelling healthcare organizations to rapidly adopt digital solutions for remote patient care (Ali & Khan, 2023; Kum et al., 2024). Extant literature increasingly recognizes this phenomenon, with substantial research examining the implementation and impact of various IT solutions in healthcare (Baker & Xiang, 2023; Balasubramanian et al., 2023).

With the evolving digital healthcare landscape, immersive technologies have emerged as transformative solutions that transcend traditional healthcare technologies. Traditional healthcare technologies comprise long-established technological systems that have underpinned clinical practice for decades and continue to function as the primary digital infrastructure in numerous healthcare settings worldwide. These fundamental technologies include electronic health records (EHR) (Baltrusaitis et al., 2018; White Baker et al., 2023), standard telemedicine platforms (Baker & Stanley, 2018), traditional medical imaging technologies (Marias, 2021), and biometric monitoring systems (Fatima et al., 2019). Traditional healthcare IT has primarily focused on information management, data storage, and basic communication frameworks, with limited capacity for immersive user engagement (Azita et al., 2014; Aceto et al., 2018). Unlike these traditional systems, immersive technologies, encompassing virtual reality (VR), augmented reality (AR), and mixed reality (MR), create unprecedented experiences that fundamentally transform healthcare delivery (Suh & Prophet, 2018). Immersive technologies in healthcare are defined as technologies that blur the boundary between physical and virtual worlds, enabling users to experience a sense of immersion in synthetic environments where physical and virtual objects coexist (Yeung et al., 2021). These synthetic environments refer to computer-generated three-dimensional spaces that simulate real or imaginary settings, allowing users to interact with virtual elements and experience a sense of presence within these artificially constructed realities (Benford et al., 1998; Abdelguerfi, 2001). Immersive technologies in healthcare are distinct in their ability to generate realistic, interactive virtual environments that enable spatial presence, enhanced telepresence, and multi-modal interactions (Suh & Prophet, 2018). This technological paradigm facilitates advanced capabilities such as virtual surgical planning with haptic feedback, three-dimensional patient data visualization during consultations, and immersive therapeutic interventions (Huang et al., 2024). The application scope extends to medical education, surgical simulation, pain management, and remote patient monitoring, offering solutions that conventional healthcare IT cannot replicate (Petersen et al., 2022; Wang et al., 2024; Einloft et al., 2024). A notable real-world implementation can be seen in India, where Bhattacharya et al. (2022) report that 'Apollo Hospitals collaborates with 8chili Inc to enter the Metaverse' and 'AIIMS, New Delhi implemented new digital surgery technology from Immersive Touch. The unique attributes of immersive technologies challenge the existing understanding of healthcare IT adoption and implementation, necessitating a theoretical perspective that captures the unique technological and contextual issues of immersive technology adoption. This study addresses this gap by examining the factors contributing to immersive technology adoption in healthcare settings.

For this purpose, this research draws upon the integrated view of the Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory. Technology adoption models such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of

[1] Fortune Business Insights. (2025). Digital health market size, share & industry analysis, 2032. Retrieved March 3, 2025, from https://www.fortunebusinessinsights.com/industry-reports/digital-health-market-100227

Technology (UTAUT), while valuable for understanding IT implementation, primarily focus on individual-level acceptance factors (Venkatesh et al., 2003; Hennington & Janz, 2007; Holden & Karsh, 2010). The TOE-DOI integration offers a more nuanced understanding that encompasses both the innovative characteristics of immersive technologies and the complex organizational, environmental, and social factors critical to their adoption in healthcare settings (Depietro et al., 1990; Rogers, 2010). This theoretical synthesis is particularly relevant for examining immersive technology adoption in emerging economies like India, where healthcare challenges are compounded by infrastructure limitations, resource constraints, and unique socio-cultural factors (Ugargol et al., 2023; Joshi et al., 2023; Mehta et al., 2024). Given this complex theoretical and practical landscape, this research addresses two questions:

RQ1: What are the key facilitators influencing the adoption of immersive technologies in the healthcare service?

RQ2: How do these facilitators interrelate/interact?

This study employs the grey-DEMATEL method, which integrates the Grey theory's capacity to handle uncertain information through interval numbers (Ju-Long, 1982) with DEMATEL's ability to analyze causal relationships among complex system factors (Gabus & Fontela, 1972). This integrated approach is particularly valuable for examining healthcare technology adoption where decision environments feature both interdependent relationships and information uncertainty (Singh et al., 2022; Kumar Singh et al., 2024). The Indian healthcare context provides a rich setting for this investigation, given its significant challenges in healthcare accessibility, infrastructure adequacy, and service delivery efficiency (Croke et al., 2024). With approximately 65% of its 1.4 billion population residing in rural areas (Kamath et al., 2022).

Immersive technologies offer potential solutions to these challenges through virtual training, remote consultation, and enhanced medical education capabilities. For instance, VR simulations enable healthcare professionals to replicate various medical procedures during training without involving physical resources or patients (Kennedy et al., 2023; Elsenbast et al., 2024). Similarly, AR applications can improve surgical accuracy by overlaying computer data onto real-world image space to assist surgeons in orientation and planning during surgeries (Huang et al., 2024). Moreover, these technologies can coexist and synergize with other existing solutions, enhancing the delivery of more immersive remote consultancies (Verhey et al., 2020).

This research contributes significantly to both theory and practice. Theoretically, it advances the understanding of immersive technology adoption in healthcare by integrating TOE and DOI perspectives with empirical insights from the Indian context. Practically, the findings provide healthcare organizations and policymakers with actionable insights for the successful implementation of immersive technologies, particularly in resource-constrained environments. The grey-DEMATEL analysis offers a structured approach to prioritizing adoption factors and understanding their interdependencies, enabling more effective strategic planning and resource allocation.

The remainder of this paper is structured as follows: First, a review of the relevant literature and the framework is presented. Next, the research methodology is described, including the data collection and analysis procedures. The findings are then presented and discussed in relation to their implications. Finally, the paper concludes by summarizing the contributions, acknowledging the limitations, and suggesting directions for future research.

2 Literature Review

The literature on immersive technologies in healthcare explores the drivers of their adoption and impact, particularly in the Indian healthcare context. It examines the ongoing digital transformation in healthcare systems, highlighting the increased use of advanced technologies such as wearables, telemedicine, virtual reality, and artificial intelligence. The shift from traditional to immersive technologies is discussed, focusing on the applications and benefits of virtual reality (VR), augmented reality (AR), and mixed reality (MR) in healthcare settings. These technologies are shown to improve medical education, enhance surgical planning, manage pain more effectively, and provide better patient care. The literature emphasizes how these technologies are reshaping various aspects of healthcare, from clinical practice to medical training, and highlights their potential to address some pressing challenges in healthcare delivery.

2.1 Technology Adoption in Healthcare

Traditional technologies in healthcare, such as health data management systems, including Electronic Medical Records (EMRs) (Yaqoob et al., 2022; Tapuria et al., 2021) and Patient Health Records (PHRs) (Bouayad et al., 2017; Iakovidis, 1998) have streamlined data management and improved clinical decision-making. Additionally, self-diagnosis tools such as blood pressure and blood sugar monitors have empowered patients to monitor their health conditions independently. Advanced diagnostic systems, including MRI scanners (Schaap et al., 2014), CT scanners (Silva et al., 2011), and X-ray machines, have revolutionized disease detection and medical imaging. Furthermore, care delivery systems, such as hospital dashboards (Baskett et al., 2008) have enhanced operational efficiency in healthcare facilities.

The COVID-19 pandemic accelerated the adoption of immediate healthcare technologies to maintain patient well-being during lockdowns and foster innovation in the medical sector (Ali & Khan, 2023; Kum et al., 2024; Balasubramanian et al., 2023). As a response, many healthcare organizations have increasingly turned to emerging technologies and AI-based solutions to engage patients and develop new business models (Kumar et al., 2024; Lepore et al., 2023; Al Dahdah & Mishra, 2023). The widespread use of the internet and digital platforms has further facilitated technology adoption, making healthcare one of the most technologically driven industries (Kraus et al., 2021). With rapid advancements in digital health solutions, including AI-powered tools and high-speed connectivity, the healthcare landscape is undergoing a transformation toward intelligent and automated systems. AI-driven applications assist in prognosis, diagnosis, and disease management through data mining and pattern recognition (Göndöcs & Dörfler 2024). Additionally, the deployment of 5G technology enables real-time, uninterrupted communication, facilitating remote healthcare access and virtual consultations (French et al., 2020). AI's ability to process vast amounts of healthcare data efficiently is also contributing to better clinical decision-making and personalized treatment plans (Reddy, 2018; Wang et al., 2018).

Table 1. Adoption of Different Technologies in Healthcare

Authors	Technology	Context	Factors	Theories
(Chau & Hu, 2002)	Telemedicine	Adoption of telemedicine technology	Attitude, Subjective norm, PBC	Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB)
(Øvretveit et al., 2007)	Electronic medical record	Implementation of IT in healthcare	Consultation before implementation, Consensus about need, Prioritization by management, Competent IT team, Tried and tested system, User-friendly, Potential for development, Easy order entry. Hindering factors: Recent merger, Time constraints, Difficulty involving doctors, Cost disagreements. Impact: No extra time burdens, Increased efficiency, Better coordination of long-term patients	Theory of Information Technology Implementation
(Wu et al., 2009)	Information technology	Influence on IT–healthcare partnerships	Healthcare organization overview, External knowledge networking, Management and interpersonal skills, Healthcare technology integration, Attitudes to develop partnerships	Social Cognitive Theory, Empowerment Theory
(Pai & Huang, 2011)	Healthcare information systems	Intention to use healthcare information systems	Information quality, Service quality, System quality	Behavior Theory, Technology Acceptance Model
(Venkatesh et	E-healthcare	Implementation	Network position, Quality of	Social Network

al., 2011)		of Electronic Healthcare System	care, Electronic healthcare system use	Theory
(Avancha et al., 2012)	Mobile computing tech	Adoption of mobile health technology	Openness and Transparency, Purpose Specification, Collection Limitation, Use Limitation, Individual Participation, Data Quality, Security, Accountability, Patient Access, Anonymity	Conceptual Privacy Framework
(Ancker et al., 2012)	Health information tech	Adoption of health IT systems	Healthcare organization, Healthcare provider user, Patients receiving care	Sociotechnical Theory
(Phichitchaisopa & Naenna, 2013)	Healthcare IT	Adoption of healthcare IT	Performance expectancy, Effort expectancy, Facilitating conditions as significant determinants of users' behavioral intention	Unified Theory of Acceptance and Use of Technology (UTAUT)
(Chong et al., 2015)	RFID	RFID adoption in healthcare supply chain	Performance expectancy, Effort expectancy, Facilitating conditions, Social influence, Personality traits, Demographic characteristics	Unified Theory of Acceptance and Use of Technology (UTAUT)
(Rahman et al., 2016)	Healthcare Technology Self-Efficacy	Influence on Individual Attitude of Healthcare Tech	General Self-Efficacy (GSE) and Computer Self-Efficacy (CSE)	Social Cognitive Theory
(Ruiz Morilla et al., 2017)	E-health	Physicians regarding e-health	Previous participation in Telemedicine projects, Knowledge of technological possibilities, Personal use of technology (2.0 philosophy), Workplace integration and support, Healthcare system readiness, Evolution of the physician-patient relationship	Diffusion of Innovation
(Cheung et al., 2019)	Wearable healthcare tech	Adoption of Wearable Healthcare Tech	Reference group influence, Consumer innovativeness, Health belief, Health information accuracy, Perceived usefulness	Diffusion of Innovation
(Talukder et al., 2020)	Wearable Healthcare Tech	Antecedents of Wearable Healthcare Tech Acceptance	Social influence, Performance expectancy, Functional congruence, Self-actualization, Hedonic motivation	Unified Theory of Acceptance and Use of Technology
(Kelly et al., 2020)	Internet of Things (IoT)	Impact of IoT in Healthcare Delivery	Policy Support, Technology Accessibility, Cybersecurity Guidelines	-
(Hossain et al., 2021)	Internet of Things	Adoption model of continuous glucose monitoring	Interpersonal Influence, Personal Innovativeness, Trustworthiness, Attitude Toward Wearables, Self-Efficacy, Health Interest, Perceived Value, Intention to Use	Technology Acceptance Model, Self-Efficacy Theory, Theory of Reasoned Action, Theory of Planned Behavior

(Sebastian et al., 2023)	Artificial Intelligence	AI product adoption among patients	Privacy Concerns, Trust, Consumer Innovativeness, Novelty Value	-
(Onitilo et al., 2023)	Voice recognition tech	Adoption of voice recognition tech in rural healthcare	Institutional factors	-
(Rony et al., 2024)	Artificial Intelligence	AI adoption in healthcare: Nurses' perspectives	Ethical concerns, Privacy challenges, Balancing innovation and ethics, Human touch vs. technology, Patient-centered care, Ethical preparedness	-
(Al-Rawashdeh et al., 2024)	Smart Healthcare	IoT applications in nursing care	Effort Expectancy, Performance Expectancy, Anxiety, Trust, Top Management, IT Knowledge, Technology Awareness, Perceived Severity, Social Influence	UTAUT Model, Health Belief Model (HBM), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB)

With the growing literature on healthcare technology adoption, Table 1 highlights various studied technologies, including telemedicine, electronic medical records, and e-healthcare, across contexts such as IT implementation, RFID adoption, wearable tech, AI, and IoT in healthcare. However, the adoption of immersive technology in healthcare remains largely unexplored. This study addresses this gap by examining its role in enhancing medical training, patient engagement, and treatment outcomes, offering insights into its benefits, challenges, and broader implications for healthcare.

2.2 The Transformative Power of Immersive Technologies in Healthcare

Beyond conventional digital tools, **immersive technologies such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) are emerging as transformative forces in healthcare.** The transformation from traditional to immersive technologies marks a significant shift in healthcare services, revolutionizing medical education, training, and patient care (Gandolfi et al., 2024). Immersive technologies, characterized by their ability to blend real and virtual environments, provide innovative solutions for complex medical procedures, improving accuracy, engagement, and overall efficiency (Witmer & Singer, 1998; Suh & Prophet, 2018; Handa et al., 2012; Ferguson et al., 2024). To conceptualize the scope of immersive technology, Milgram and Kishino (1994) and Mohammadhossein et al. (2024) introduced the reality-virtuality continuum, which categorizes different immersive experiences. Augmented reality (AR) overlays virtual elements in the real world, while virtual reality (VR) fully immerses users in a digitally simulated environment. Mixed reality (MR) integrates digital and real-world elements, allowing seamless interaction between the two. These technologies collectively form extended reality (XR), encompassing AR, VR, MR, and related innovations, expanding the potential of digital healthcare solutions (Suh & Prophet, 2018).

Immersive technologies' growth in the healthcare sector presents a lucrative and promising future in reforming the sector on various fronts (Combalia et al., 2024). Through the help of these virtual environments, medical procedures can be evaluated in a situation where the individuals performing those procedures are guided or supervised by experts, thus leading to improved training and skill development solutions (Kim et al., 2023). Furthermore, installing the touch sensors and the haptic information allows for detecting painful reactions and feelings, which are crucial for understanding the patient's state (Huang et al., 2024) Additionally, wearable devices, including trackers and smartwatches, assist in remote patient monitoring by ensuring that real-time information is relayed efficiently to the caregiver, hence enabling early action to be taken when a patient develops certain conditions such as irregular heartbeat or fluctuations in blood pressure (Ali et al., 2021).

The implementation of immersive technologies in healthcare presents significant opportunities but also faces several challenges that may be addressed for adoption. Wang et al. (2020) identify key risks in healthcare delivery contexts, including reduced transparency, inequitable distribution of clinical services, and inadequate algorithm regulation. Patient resistance represents another barrier, as many individuals are accustomed to traditional in-person consultations and may question the quality of virtual care (Prakash & Das, 2021). The implementation challenges span multiple dimensions: social aspects (including connectivity issues and legislative concerns), design considerations (including system performance and cost-effectiveness), and security requirements (ensuring device and data protection, addressing privacy concerns, and managing third-party data access). Garrett et al. (2014) further highlight fundamental challenges in clinical VR applications, including theoretical underdevelopment, lack of standardized technical specifications, difficulties distinguishing between media effects versus medium effects, in vivo concerns, and cost barriers. These multifaceted challenges underscore the need for a comprehensive approach to managing immersive technology adoption in healthcare settings.

The adoption of artificial intelligence and virtual care is growing, signifying the focus of the current leadership in the healthcare industry to take advantage of technological advancement to create value[2]. In addition, networks and partnerships with Indian hospitals and the government, as well as collaborations with technology leaders like Google, Microsoft, and IBM, help formulate and advance plans for using artificial intelligent networks[3]. Such affiliations are meant to use innovative solutions to treat diseases, increase the availability of medical services, and advance the state of the patient experience. Therefore, this type of partnership can act as the facilitator to uptake immersive technologies that provide the required skills, facilities, and support structures. As the Indian healthcare system gears up to increase its adoption of digital solutions, immersive technologies have a massive stake in the process (Shardeo et al., 2024; Mohsen & Alangari, 2024). These technologies present capabilities not found in traditional models, which can overcome the problems present in the Indian healthcare system, such as an abundance of trained workers, lack of skilled medical care, especially in rural areas, and insufficient and poor medical training and learning methods.

3 Framework for Immersive Technology Adoption in Healthcare

Adopting immersive technologies in healthcare represents a complex socio-technical phenomenon requiring theoretical grounding. Healthcare organizations operate within intricate environments characterized by diverse stakeholders, regulatory requirements, and resource constraints. These complexities necessitate a theoretical foundation that can adequately capture both technological and contextual dimensions of adoption.

Prior research demonstrates significant limitations in applying singular theoretical perspectives to healthcare technology adoption (Lapointe & Rivard, 2005; Holden & Karsh, 2010). Research in healthcare technology adoption indicates that while various theories examine adoption processes, selecting appropriate theoretical frameworks considers both technology characteristics and implementation context (Agarwal et al., 2010). Traditional technology adoption theories demonstrate notable constraints when applied to healthcare contexts. The Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) primarily emphasize individual perceptions of usefulness and ease of use. However, these models prove insufficient for examining organizational-level adoption of complex healthcare technologies, as they neglect crucial organizational and environmental factors characteristic of healthcare institutions (Chau & Hu, 2002; Gagnon et al., 2016).

Based on their complementary strengths and specific applicability to healthcare technology adoption, this study employs an integration of the Diffusion of Innovation theory and the Technology-Organization-Environment framework.

3.1 The Diffusion of Innovation Framework

The DOI theory, developed by Rogers (2010), offers particular relevance for examining immersive technology adoption in healthcare through its focus on innovation characteristics and adoption patterns at multiple organizational levels. Prior research demonstrates DOI's efficacy in analyzing healthcare

[2] Please refer to Philips Future Health Index 2023 report: Taking healthcare everywhere [PDF file]. Retrieved July 17, 2024, from https://www.philips.com/c-dam/corporate/newscenter/global/future-health-index/report-pages/experience-transformation/2023/first-draft/philips-future-health-index-2023-report-taking-healthcare-everywhere-global.pdf

[3] Please refer to National Strategy for Artificial Intelligence [PDF file]. Retrieved July 17, 2024, from https://www.niti.gov.in/sites/default/files/2023-03/National-Strategy-for-Artificial-Intelligence.pdf

technology adoption across diverse institutional settings (Chau & Hu, 2002; Gagnon et al., 2016). DOI theory identifies several key elements influencing organizational innovation adoption. Leadership attitudes and organizational readiness significantly impact adoption decisions, particularly relevant in healthcare where clinical leadership often determines technology implementation success. Structural characteristics, including centralization and complexity, shape how healthcare institutions process and implement technological innovations. External system interactions influence organizational receptivity to new technologies, especially pertinent given healthcare's interconnected nature.

In the Indian healthcare context, these elements prove especially relevant given the sector's hierarchical structure and diverse institutional arrangements. These elements include leadership attitudes and organizational readiness, structural characteristics such as centralization and complexity, and external system interactions with environmental factors (Sulaiman & Wickramasinghe, 2014). DOI theory enables examination of how immersive technologies diffuse through different types of healthcare organizations while accounting for varying resource constraints and technological capabilities.

3.2 Technology-Organization-Environment Framework

The TOE framework, introduced by Tornatzky and Fleischer (1990), extends theoretical analysis by examining contextual dimensions crucial for healthcare technology implementation. Research demonstrates TOE's value in analyzing healthcare technology adoption across different national and organizational contexts (Sulaiman & Wickramasinghe, 2014). The framework's structured examination of technological, organizational, and environmental contexts provides essential analytical depth.

Within the technological context, TOE examines both existing infrastructure capabilities and emerging technological requirements. This proves particularly relevant when considering immersive technology implementation in resource-constrained healthcare settings. The organizational context addresses structural and process characteristics that influence adoption decisions, including resource availability and institutional protocols. Environmental context examines external factors such as regulatory requirements and market conditions that shape technology adoption choices.

3.3 Theoretical Synthesis

The integration of DOI and TOE frameworks provides several advantages for examining immersive technology adoption in Indian healthcare. The theoretical synthesis enables multilevel analysis spanning individual, organizational, and environmental factors while maintaining analytical coherence. Furthermore, the integrated framework captures both generic adoption factors and context-specific elements unique to Indian healthcare, including cultural and social dimensions affecting technology acceptance, resource and infrastructure constraints, regulatory requirements specific to Indian healthcare, and organizational diversity across public and private institutions (Chandra & Kumar, 2018). This integrated theoretical approach advances the understanding of healthcare technology adoption in several ways. The framework provides a structured analysis of contextual factors while enabling the examination of adoption patterns across organizational types. Additionally, it incorporates cultural and institutional dimensions particularly relevant to emerging economies while addressing implementation challenges specific to resource-constrained settings (Jia et al., 2017; Larosiliere et al., 2017).

Cultural and social dimensions affecting technology acceptance receive particular attention through this theoretical lens. Resource and infrastructure constraints characteristic of emerging economy healthcare systems find thorough examination through the integrated framework. Regulatory requirements specific to Indian healthcare and organizational diversity across public and private institutions receive systematic analysis through this theoretical approach. Prior research validates this theoretical integration for examining healthcare technology adoption in emerging economies. The framework proves particularly suited for analyzing immersive technology implementation given the technology's transformative potential and unique adoption challenges in resource-constrained settings. Through this integrated theoretical lens, the study examines how healthcare organizations evaluate, adopt, and implement immersive technologies while accounting for both innovation-specific and contextual factors.

4 Selection of Facilitators

Expanding on the Diffusion of Innovation (DOI) and the Technology-Organization-Environment (TOE) framework, this study aims to determine inhibitors and promoters in integrating immersive technologies in healthcare. The study identified five crucial characteristics that influence the acceptance and implementation of immersive technology in the healthcare sector in India.

4.1 Technology Factors

The technology category, derived from the TOE framework, is further subdivided based on the DOI theory's characteristics of innovations: Relative Advantage, Compatibility, and Complexity are some of the most well-known models based on the diffusion of innovation theory. Thus, these subcategories provide the framework for analyzing the technological factors that define adoption.

Relative Advantage is one of the factors in the DOI theory, where three major driving forces are proposed for realistic environments such as healthcare using immersive technologies. The first facilitator, Immersive Tech Interactivity with Pain Management, spotlights the level of interaction with such technologies and opportunities to offer immersive experiences to distract the pain sensations. It provides an opportunity to decrease pain-relieving medication usage and reduce their side effects in managing patients' pain (Chuan et al., 2021). In the Indian healthcare context, these pain management applications hold particular value in addressing the urban-rural divide, where specialists may take 30-60 minutes to arrive in rural settings (Kumar et al., 2019). Precision Surgical Guidance is the second factor that enhances the utilization of augmented reality (AR). By positioning the essential data directly within the surgeon's field of view, the augmented reality (AR) system might enhance surgical accuracy, reduce the duration of procedures, and limit invasiveness (Ma et al., 2019). The third facilitator, Cognitive Health Sculpture, concentrated on utilizing immersive technology to create captivating and efficient cognitive health interventions. Customized and adaptable interventions can be developed to target specific cognitive domains, which is a more effective strategy for cognitive training compared to a generic approach (Suh & Prophet, 2018).

Compatibility, a critical feature of the DOI theory, is characterized by two essential facilitators: Interoperability with existing systems and EHR-compatible AR/VR technologies. Villarreal et al. (2023) emphasize the importance of integrating immersive technology into existing systems, addressing data-sharing concerns, and aligning with the present workflow to effectively enhance patient care. Due to the compatibility of various AR and VR applications with electronic health records systems, it is convenient to record the usage of these applications and access valuable information from the records. This enhances the value of such applications in healthcare organizations.

Complexity, which falls under the broader topic of Technology, includes user-friendliness, data security, and privacy as significant factors. Mäkinen et al. (2022) contend that the integration of immersive technology in healthcare should prioritize user-friendliness, enabling medical personnel to utilize it effortlessly with minimal instruction. This technique has the potential to greatly improve the efficiency of workflow and increase the adoption of these technologies. In addition, Ali et al. (2023) emphasize the significance of developing strong data security mechanisms to safeguard patient information and maintain compliance with privacy rules. Healthcare organizations can effectively encourage immersive technologies that simplify healthcare processes by addressing these concerns connected to complexity.

4.2 Organizational Factors

The organizational category of the TOE framework encompasses various crucial facilitators that assess the internal preparedness and capability of healthcare organizations to facilitate the utilization of immersive technologies. Parasuraman (2000) defines Technology Readiness as the inclination of individuals to adopt and utilize technology to achieve their objectives, both in public and private domains.

The Diffusion of Innovation hypothesis (DOI) is a commonly employed adoption model in Information Systems (IS) research (Weigel et al., 2014). The DOI hypothesis assumes that specific characteristics of both individuals and organizations serve as indicators of their amount of innovativeness at the organizational level. This, in turn, influences the adoption of new IT innovations. The diffusion of innovation theory is highly applicable when examining the acceptance of immersive technology in healthcare, as immersive technology represents an innovation within the healthcare domain. A study by Lanseng and Andreassen (2007), Galetsi et al. (2023), and Zhang and Zhao (2024) confirmed that perceived technological utilitarian attitudes predominate in consumers who have a high degree of technological orientation, especially concerning the perceived usefulness and ease of use of self-diagnosis activity.

Training and education also come out strongly as another influential factor in this category. Gutierrez-Bucheli et al. (2024) and Liu et al. (2021) note that it is crucial to offer adequate training and education on the different immersive technologies to support optimal functioning in healthcare facilities. This is especially relevant in the Indian medical education system, which traditionally emphasizes theoretical knowledge over hands-on training, creating a unique organizational need for immersive technologies that can function within India's existing healthcare infrastructure (Ramachandra et al., 2020). Healthcare professionals can have a safe practice environment to enhance their performance through hands-on practice, this also affords patients unique therapeutic interventions that meet their individual needs.

Another major factor is that leadership support is crucial in effectively implementing immersive technologies. According to Thong (1999), the top manager supports the overall vision development and shares the importance of the new technologies with the other firm members. This support is equally important in maintaining the value of potential change and the pace of the adoption process.

An additional requirement related to the concept of organizational facilitators is flexibility or adaptability to change. It is worth underlining the necessity of developing approaches that focus on overcoming resistance and enabling a smooth transition to enhance individual flexibility (Alkraiji et al., 2013). This approach is particularly important in countering the forces of organizational inertia and introducing a culture that accepts and champions technological advancement.

Evaluation and feedback form the last section of the organizational facilitators. Pears et al. (2020) stress the need for constant feedback and positive reinforcement when implementing immersive technology in healthcare settings. This constant assessment means that the application of immersive technology is being adapted and optimized in real-time.

4.3 External Task Environment Factors

The external task environment category refers to external factors that impact the decisions made in the adoption effort but are not controlled by healthcare organizations. Regulatory support, which includes government participation and support, facilitates this category. While considering the external environment to integrate innovative technologies in healthcare, Chang et al. (2007) classified government policy as an issue to be concerned about. The Medical Council of India's curriculum reforms emphasizing competency-based training create a particularly favorable regulatory environment for immersive technologies adoption in India, addressing the specific challenges of maintaining patient safety standards in high-volume healthcare settings characteristic of the Indian system (Datta et al., 2012; Jacob, 2019). Recognizing governmental policies and their dedication to public health and preventive care might also be crucial in enabling the use of immersive technologies in healthcare environments.

Collaboration and partnership are recognized as important facilitators in the external task environment. Regarding the use of immersive technologies, Brown et al. (2010) and Cook et al. (2019) recognized and examined the relationship between partnerships and collaborations. These collaborations can speed up the adoption process by providing access to information, resources, and hands-on support that independent healthcare organizations might not have.

Integrating the DOI theory and TOE framework, this comprehensive theoretical framework provides a view of the facilitators influencing the adoption of immersive technologies in the Indian healthcare system.

Table 2. Facilitators of Immersive Technology Adoption in Indian Healthcare System

TOE Framework (Depietro et al., 1990)	**Determinants**		**Facilitators**	**Facilitator definitions**	**Authors**
			Immersive tech interactivity with Pain Management (F1)	Utilizes immersive environments to stimulate sensory experiences for pain management during medical interventions, improving patient comfort.	Chuan et al., (2021)
Technology	DOI	Relative Advantage	Precision Surgical Guidance(F2)	Utilizes advanced technology to provide real-time guidance and	Expert opinion

	(Rogers, 2010)			visual overlays during surgical procedures, enhancing accuracy and safety.	
			Cognitive Wellness Sculpture(F3)	Facilitates cognitive rehabilitation and mental wellness interventions through interactive and immersive experiences.	Expert opinion
		Compatibility	Interoperability with existing systems(F4)	Compatibility and interoperability with existing healthcare systems.	(Villarreal et al., 2023)
			EHR-compatible AR/VR solutions(F5)	AR and VR applications that can seamlessly integrate with Electronic Health Records systems, facilitating easy documentation and data retrieval.	Expert opinion
		Complexity	User-friendliness(F6)	Design for intuitive use by medical professionals with minimal training.	(Mäkinen et al., 2022)
			Data security and privacy(F7)	Implementation of measures to protect patient data and ensure compliance.	(Ali et al., 2023)
Organization			Technology Readiness(F8)	The propensity to embrace new technology for accomplishing goals	Parasuraman, 2000; Galetsi et al., 2023; Zhang & Zhao, 2024; Montazeri et al., 2023; Hsieh, 2023
			Training and Education(F9)	Provision of comprehensive training programs for effective usage.	Gutierrez-Bucheli et al., 2024; Liu et al., (2021)
			Leadership support(F10)	Provision of resources, funding, and guidance for adoption.	Pears et al., 2020; Chang et al., 2007
			Adaptability to change(F11)	Implementation of strategies to address resistance and ensure smooth transitions.	(Alkraiji et al., 2013)
			Evaluation and feedback(F12)	Establishment of regular evaluation and feedback mechanisms.	(Pears et al., 2020)
External task environment			Regulatory support (Government support| Government involvement) (F13)	Assurance of compliance with standards and legal requirements.	Chang et al., 2007; Yang et al., 2015
			Collaboration and partnerships(F14)	Facilitation of adoption through partnerships and collaborations.	Brown et al., 2010; Cook et al., 2019

5 Research Methodology

In today's complex and interconnected systems, decision-making is critical in various fields, including emergency management, organizational strategies, and technology adoption (Sharmin et al., 2024). The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is a widely used technique for analyzing the interrelationships between factors in complex systems. However, real-world scenarios often involve various environments, encompassing qualitative information that can lead to subjective human judgments and imprecise data. Researchers have proposed several approaches to address the limitations of traditional decision-making methods. Bansal et al. (2014) advocate integrating a fuzzy approach into decision-making to address uncertainties and mitigate inappropriate human judgment. However, the fuzzy approach also has its limitations.

Grey system theory offers advantages over fuzzy systems as it can accommodate conditional fuzziness (Zadeh, 1965; Li et al., 2007; Khan et al., 2024). Recognizing these benefits, researchers such as Singh et al. (2022) have integrated the grey approach with DEMATEL to better handle uncertainty and incomplete information in decision-making processes. This integration aims to overcome the limitations of DEMATEL alone, which can be ineffective when dealing with the fuzziness and bias introduced by complex real-world factors.

The following subsections discuss grey theory and the DEMATEL technique.

5.1 Grey Approach

Black signifies undisclosed information about the system, while white indicates full disclosure. Real-life systems often fall between these extremes, neither entirely transparent nor completely opaque. The grey theory, pioneered by Ju-Long (1982), proves invaluable in addressing such situations. This theory is particularly suited for discrete datasets originating from multiple sources and for systems with limited and inadequate information (Wang, 2004; Tseng, 2009). It finds significant utility in group decision-making processes (Liu & Qiao, 2014; Chakraborty et al., 2023) and extrapolates insights from small datasets (Fu et al., 2012). Grey theory has found successful applications in various domains such as finance, tourism, integrated circuit industry, airline network design, automotive parts remanufacturing, and waste utilization industry (Wang, 2004; Jin et al., 2012; Samvedi & Jain, 2013; Xia et al., 2015; Bo et al., 2024).

The modified-CFCS (Converting Fuzzy Data into Crisp Scores) method can also translate grey data into precise numerical values (Zhu et al., 2011; Kumar Singh et al., 2024). To calculate the crisp value from a grey $\varphi p_{ij}^{m} = [\underline{\varphi} p_{ij}^{m}, \overline{\varphi} p_{ij}^{m}]$ number, refer to the following steps:

Step 1: Normalization

$$\underline{\varphi}\overline{p}_{ij}^{m} = (\underline{\varphi} p_{ij}^{m} - \underbrace{min}_{j} \underline{\varphi} p_{ij}^{m}) / \nabla_{min}^{max} \tag{1}$$

$$\overline{\varphi p}_{ij}^{m} = (\overline{\varphi} p_{ij}^{m} - \underbrace{min}_{j} \underline{\varphi} p_{ij}^{m}) / \nabla_{min}^{max} \ , \tag{2}$$

Where, $\nabla_{min}^{max} = \underbrace{max}_{j} \overline{\varphi} p_{ij}^{m} - \underbrace{min}_{j} \underline{\varphi} p_{ij}^{m})$

Step 2: Determining normalized crisp value

$$q_{ij}^{m} = \frac{\underline{\varphi}\overline{p}_{ij}^{m}\left(1 - \underline{\varphi}\overline{p}_{ij}^{m}\right) + \overline{\varphi} p_{ij}^{m} \times \overline{\varphi p}_{ij}^{m}}{1 - \underline{\varphi} p + \overline{\varphi p}_{ij}^{m}} \tag{3}$$

Step 3: Calculation of final crisp value

$$r_{ij=}^{m} \underbrace{min}_{j} \underline{\varphi} p_{ij}^{m} + q_{ij}^{m} \nabla_{min}^{max} \tag{4}$$

Table 3. Mathematical Symbols for the Grey Approach (Source: Singh et al., 2022)

Symbols	Depiction
$\boldsymbol{M}$	The number of specialists (experts);
$\boldsymbol{I}, \boldsymbol{J}$	List of facilitators' indices;
$\varphi \boldsymbol{p}_{ij}^{m}$	The grey number is given by the specialist m, which represents the influence of criterion i on the criterion j, $i \in I, j \in J, m \in M$;
$\boldsymbol{q}_{ij}^{m}$	Normalized crisp value for specialist m, where $i \in I$, $m \in M$;
$\boldsymbol{r}_{ij}^{m}$	Final crisp value for specialist m, where $i \in I$, $m \in M$;
$\boldsymbol{C}$	The initial relation matrix, where $C = [c_{ij}]_{i \times j}$, c_{ij} denotes the influence of the criterion i on the criterion j;

5.2 The DEMATEL

Gabus and Fontela (1972) utilized DEMATEL in late 1971 at the Battelle Memorial Institute, Geneva Research Center. This method analyzes complex systems and understands the interdependencies among different factors (Xue et al., 2024). Using the DEMATEL method, decision-makers can visually represent and evaluate cause-effect relationships between factors, prioritizing critical components in a system. DEMATEL care be especially helpful in industries such as automotive and logistics, where understanding the cause-effect relationships and prioritizing projects is crucial for success (Pinto et al., 2023). Additionally, the DEMATEL technique can effectively identify key factors/barriers/facilitators and evaluate the performance of various indicators and sub-indicators in green marketing strategies, human resource management, sustainability in the supply chain through e-procurement, emergency management optimization, RFID-blockchain adoption in the Indian public distribution systems, ICT adoption in Indian MSMEs, and enterprise resource planning system selection (Chen & Yang, 2019; Priyanka et al., 2023; Ramkumar & Jenamani, 2015; Singh et al., 2022; Kumar Singh et al., 2024). The DEMATEL method provides a systematic approach to understanding and evaluating interdependencies among enablers within blockchain technology's role in the supply chain, specifically in the context of organizational adoption (Agi & Jha, 2022). The study proposed the DEMATEL tool to provide the cause and prominence interrelationships among these facilitators.

The DEMATEL process comprises the following stages:

Step 1*:* Establishment of the initial relationship matrix "C"

During this step, an initial relationship matrix is constructed, utilizing input from specialists.

$$C = \begin{bmatrix} 0 & c_{12} & c_{13} & \cdots & c_{1(n-1)} & c_{1n} \\ c_{21} & 0 & c_{23} & \cdots & c_{2(n-1)} & c_{2n} \\ c_{32} & c_{32} & 0 & \cdots & c_{3(n-1)} & c_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{(n-1)1} & c_{(n-1)2} & c_{(n-1)3} & \cdots & 0 & c_{(n-1)n} \\ c_{n1} & c_{n2} & c_{n3} & \cdots & c_{n(n-1)} & 0 \end{bmatrix} \tag{5}$$

Step 2: Create the normalized direct-relation matrix "U" using equations (6) and (7) followed to derive the normalized direct-relation matrix.

$$U = \beta * C \tag{6}$$

$$\beta = \frac{1}{\underbrace{max}_{1 \le i \le I} \sum_{j=1}^{J} c_{ij}} \tag{7}$$

Here, β represents the normalization factor.

Step 3 involves deriving the total relation matrix "F" using equation (8), where "I" represents the identity matrix.

$$F = U(I - U)^{-1} \tag{8}$$

Step 4: The sum of rows (P) and columns (S) in a matrix is computed according to equations (9) and (10), respectively.

$$P = \left[\sum_{j=1}^{J} f_{ij}\right]_{J\times 1} \tag{9}$$

$$S = \left[\sum_{i=1}^{I} f\right]_{1\times I} \tag{10}$$

Step 5 involves a prominence-causal relationship diagram based on "P-S" and "P+S" values, as depicted in Figure 2.

5.3 Integrating Grey-DEMATEL

In the outlined research framework (Figure 1), the initial stage involves pinpointing facilitators. By thoroughly reviewing the existing literature and engaging with healthcare experts in insightful discussions, this study gains valuable insights into the subject. Subsequently, the process moves on to analyzing the inter-relationships among these facilitators, as perceived by experts, using the Grey-DEMATEL technique. This analytical phase produces an initial matrix of direct relationships and the importance of facilitators using the basis of the TOE and DOI Framework. To enhance the credibility of the results, the study proposes employing sensitivity analysis as a validation measure.

6 The Application of the Proposed Framework: The Case of the Indian Healthcare Industry

In this section, the study proposes a novel approach to evaluate the facilitators of immersive technology adoption within the Indian healthcare system. Our methodology integrates the Grey-DEMATEL method, a sophisticated analytical tool that combines the strengths of Grey Systems Theory and DEMATEL. This approach is particularly well-suited to our research context, where the study aims to identify and prioritize the key facilitators driving the successful implementation of immersive technologies in healthcare. The Indian healthcare system presents a unique set of challenges and opportunities for technological innovation. Traditional evaluation methods often fall short of capturing this environment's nuanced and dynamic nature. The proposed method addresses this gap by allowing us to assess complex systems with limited or uncertain data - a common scenario in emerging technology adoption. To gain valuable insights into their interrelationships and relative importance by applying this method to the identified facilitators. This approach offers several advantages. It combines subjective expert judgments with objective data, providing a more comprehensive evaluation. It allows us to map the complex network of facilitators, revealing both direct and indirect influences (Bai & Sarkis, 2013). Furthermore, it can handle the uncertainty inherent in emerging technology adoption, particularly in a diverse healthcare system like India's. The application of the proposed model in the Indian healthcare system is done as follows:

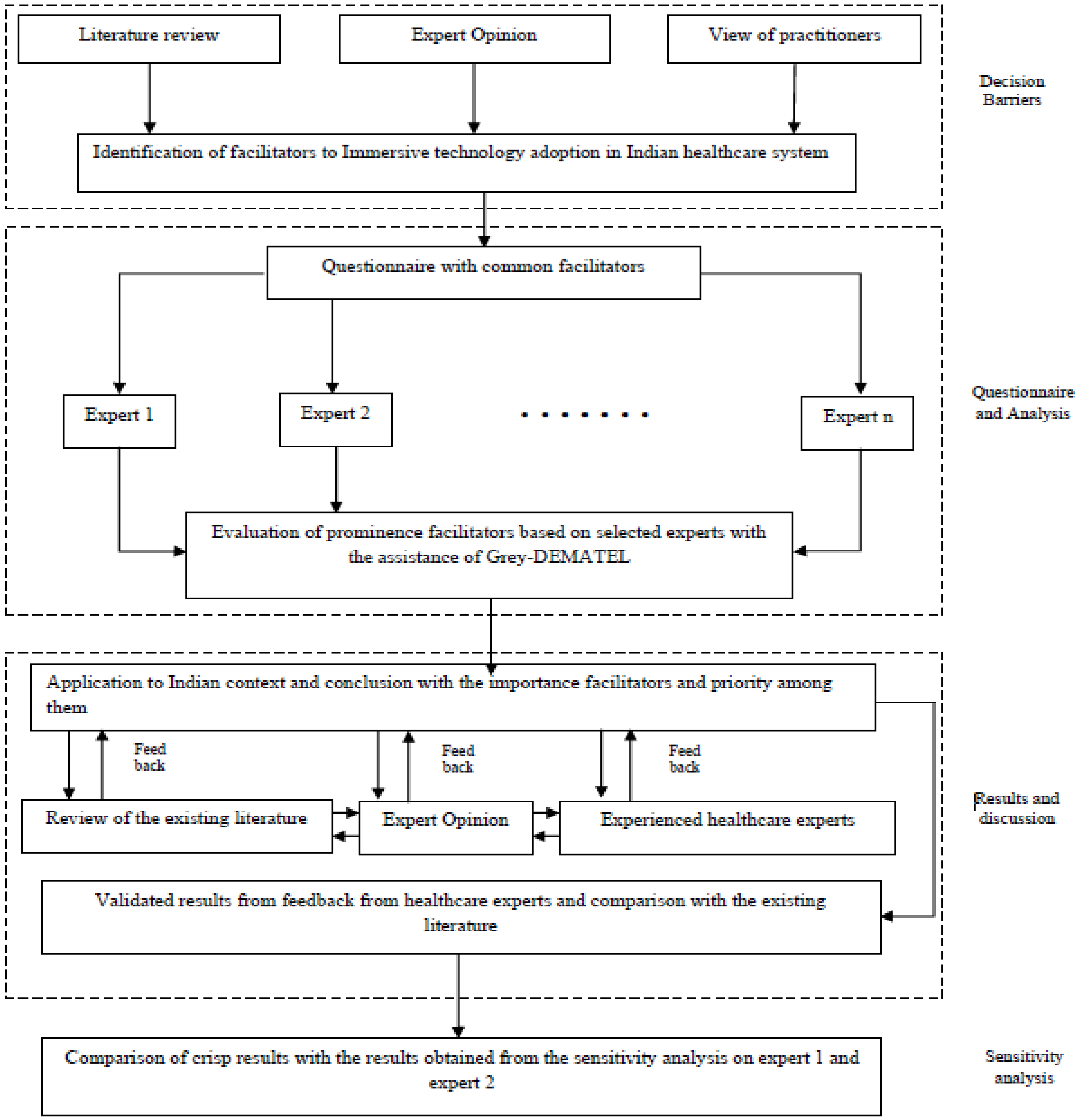

Figure 1. Research Framework (Source: Adapted from Singh et al., 2022)

6.1 Analysing Immersive Technology Adoption Facilitators

The model under investigation incorporates a comprehensive set of 14 facilitators (as detailed in Table 2), which is investigated using the grey-DEMATEL technique. This analysis involves collaborating with numerous experts to assess the relationships among these facilitators. Each expert has received a DEMATEL-based questionnaire that facilitates their comparison of interrelationships among the facilitators through pairwise assessment. The entire process of facilitator analysis unfolds in the following structured manner:

Step 1: Creating Crisp Direct-Relation Matrices for Each Expert

This initial phase involves the following four sequential steps. Firstly, the study developed a five-level scale that combines grey, linguistic, and normal values, as outlined in Table 4. Secondly, each expert receives the same questionnaire, prompting them to conduct pairwise comparisons of the relationships among the facilitators. The responses collected from the experts are meticulously recorded for subsequent analysis. Thirdly, the linguistic terms obtained from Table 4 are converted into their corresponding grayscale equivalents. Finally, utilizing equations (1)-(4), the grey values in the gathered direct-relation matrices are transformed into precise crisp values.

Table 4. The Scale for Pairwise Comparison (Source: Singh et al., 2022)

Linguistic Scale	Normal Scale	Grey Scale
No Influence (N)	0	[0, 0]
Very Low Influence (VL)	1	[0, 0.25]
Low Influence (L)	2	[0.25, 0.5]
High Influence (H)	3	[0.5, 0.75]
Very High Influence (VH)	4	[0.75, 1]

Step 2: Making an overall crisp direct-relation matrix

In Step 2, experts' weights are determined according to their expertise and experience, as detailed in Table 5. Subsequently, the weighted average method consolidates individual matrices into an overall direct-relation matrix.

Table 5. The Scale Utilized for Assigning Weights to the Experts

Linguistic Scale	Normal Scale	Grey Scale
Very Low Influence (VL)	1	[0, 0]
Low Influence (L)	2	[0.25, 0.50]
High Influence (H)	3	[0.45, 0.75]
Very High Influence (VH)	4	[0.60, 0.95]

Step 3: Normalize the overall crisp direct-relation matrix using equations (6) and (7).

Step 4: Calculate the total relation matrix using equation (8).

Step 5: Analyse Prominence and Causality with the following steps:

In step 5, Firstly, calculate the sum of each row (denoted as P_i) and each column denoted as S_j). *Whereas* P_i Represents the total influence of the facilitator i has on all other facilitators and S_j Represents the total influence all other facilitators have on the facilitator j. Then to find prominence and net effect, sum $(P_i + S_{j)}$ for each facilitator. This indicates the overall prominence (importance) of the facilitators. A higher value of $(P_i + S_{j)}$ suggests greater importance of facilitator i in its relationships with other facilitators (Singh et al., 2022; Kumar Singh et al., 2024). Then calculate the difference $(P_i - S_j)$. This indicates the net effect of the facilitator i. Additionally, a positive difference suggests that the facilitator i has a higher overall influence than it receives. A negative difference suggests that the facilitator i receives more influence than it exerts. Further to build prominence and net effect diagram and compile the prominence $(P_i + S_{j)}$ and net effect $(P_i - S_j)$ values for each factor in a table. To create a visual representation using circles or nodes for each factor, draw arrows between facilitators to show their influence on relationships.

6.2 Data Collection

The methodology detailed in the previous section has been employed in this section to evaluate the proposed model for the Indian healthcare system. Utilizing a DEMATEL-based questionnaire matrix, data was collected from four healthcare experts. The experts were selected based on their clinical experience, current involvement in healthcare delivery, and their awareness of technological developments in healthcare settings. A comprehensive literature review followed by expert consultations was conducted to identify potential facilitators for immersive technology adoption. Each expert invested over 2 hours in discussions with the authors to evaluate the facilitators within the Indian healthcare context. The study initially identified 40 facilitators through a literature review, which was subsequently consolidated and validated by the expert panel to establish a final set of 14 key facilitators most relevant to the Indian healthcare system. The panel of experts represented a diverse range of qualifications, experience levels, and familiarity with immersive technologies. The first expert is a physician with an MBBS (Bachelor of Medicine, Bachelor of Surgery) degree and a DA (Diploma in Anesthesia), bringing over nine years of experience and awareness of immersive technologies. The second expert holds an MBBS, MD (Doctor of Medicine), and Doctor of Medicine in Neurology, with seven years of experience in a medical institute setting and familiarity with immersive technologies. The third expert is a dermatologist with a Diplomate of National Board (DNB) degree, offering five years of experience but with limited familiarity with immersive technologies. The fourth expert is an MBBS doctor with 4.5 years of experience and limited exposure to immersive technologies. This diverse panel of experts provides a comprehensive perspective on the implementation of immersive technologies in the Indian healthcare system, considering both experienced experts familiar with these technologies and those with limited exposure.

The influence ratings (weights) of the experts were determined based on their experience and familiarity with immersive technologies. The first expert's extensive experience and awareness of immersive technologies contribute to their very high influence rating. The second expert's extensive medical expertise and familiarity with advanced technologies result in a high influence rating. The third expert's lack of awareness of immersive technologies leads to a low influence rating. Similarly, the fourth expert's lack of prior experience with immersive technologies also results in a low influence rating.

6.3 Results and Discussion

A thorough analysis of the facilitators identified in Phase 1 is carried out in this phase. As stated in the previous sub-section, the process involves four healthcare experts. Each expert is provided with a DEMATEL-based questionnaire matrix to compare the interrelationships between the facilitators through pairwise comparisons.

In step 1, all four experts are separately given a $(\varphi_{ij}^{k})_{14\times 14}$ questionnaire for a pairwise comparison of common facilitators to immersive technology adoption in the healthcare system. The experts' assigned weights are based on their expertise and experience, and a sensitivity analysis is performed by varying these weights, as shown in Table 6.

Table 6. Grey Scale Weights of Importance for Evaluators

Evaluators	Grey Scale			
	Main Results	Sensitivity Analysis 1	Sensitivity Analysis 2	Sensitivity Analysis 3
Expert 1	[0.60, 0.95]	[0.60, 0.95]	[0.45, 0.75]	[0.60, 0.95]
Expert 2	[0.45, 0.75]	[0.45, 0.75]	[0.60, 0.95]	[0.45, 0.75]
Expert 3	[0.25, 0.50]	[0.45, 0.75]	[0.45, 0.75]	[0.25, 0.50]
Expert 4	[0.25, 0.50]	[0.25, 0.50]	[0.25, 0.50]	[0.60, 0.95]

The linguistic scale assessment of the direct-relation matrices for Experts 1, 2, 3, and 4 is presented in Table 7 and Appendix A, B, and C, respectively.

Table 7. Direct-Relation Matrix for Expert 1

Facilitator	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
F1: Immersive tech interactivity with Pain Management	0	3	4	2	3	2	0	0	0	1	1	1	2	2
F2: Precision Surgical Guidance	1	0	1	1	1	1	2	1	2	2	2	2	2	1
F3: Cognitive Wellness Sculpture	2	2	0	3	3	2	2	2	2	2	3	3	2	2
F4: Interoperability with existing systems	1	2	2	0	2	3	1	1	1	1	2	2	2	2
F5: EHR-compatible AR/VR solutions	2	1	1	2	0	1	1	2	2	2	2	1	1	1
F6: User-friendliness	1	1	1	1	0	0	0	0	0	1	1	1	1	1
F7: Data security and privacy	2	2	2	2	1	1	0	1	1	2	2	2	1	1
F8: Technology Readiness	1	1	2	2	2	2	1	0	1	1	1	1	1	1
F9: Training and education	1	1	2	2	2	2	2	2	0	2	2	2	1	1
F10: Leadership support	2	2	2	2	2	1	1	1	2	0	3	3	3	3
F11: Adaptability to change	2	4	4	4	4	3	3	3	4	4	0	3	3	2
F12: Evaluation and feedback	1	1	1	1	2	2	2	2	1	1	1	0	1	1
F13: Regulatory support	2	4	3	4	3	3	3	3	4	4	4	4	0	3
F14: Collaboration and partnerships	4	3	2	2	3	3	2	2	2	4	4	4	4	0

After gathering expert responses, follow Steps 2 to 5, outlined in subsection 5.1, to analyze the inputs and determine the facilitators' net prominence and causal values. Step 2 combines the input matrices to create an overall direct-relationship matrix, as reported in Table 8. This matrix is then normalized using Equations 6 and 7, as reported in Table 9. Using equation 8, derive the total relation matrix and report in Table 10. Referring to Equations 9,10 (Step 4), and Step 5, computed levels of prominence (P+S) and net effect (P-S) for all the facilitators. The results are reported in Table 11.

Table 8. Overall Crisp Direct Relationships

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
F1	0.000	0.575	0.730	0.446	0.851	0.446	0.377	0.478	0.388	0.317	0.593	0.558	0.664	0.652
F2	0.353	0.000	0.447	0.447	0.447	0.447	0.733	0.647	1.027	1.027	0.840	0.733	0.933	0.647
F3	0.626	0.568	0.000	0.787	0.874	0.559	0.533	0.474	0.533	0.693	0.694	0.979	0.658	0.751
F4	0.436	0.583	0.615	0.000	0.708	0.669	0.561	0.654	0.561	0.529	0.708	0.522	0.647	0.740
F5	0.733	0.353	0.540	0.827	0.000	0.647	0.740	0.840	1.027	0.827	0.733	0.540	0.447	0.447
F6	0.537	0.595	0.502	0.443	0.295	0.000	0.388	0.447	0.447	0.635	0.728	0.787	0.693	0.693
F7	0.952	0.858	0.952	0.952	0.572	0.572	0.000	0.278	0.372	0.752	0.658	0.658	0.665	0.572
F8	0.540	0.353	0.933	0.933	1.027	1.027	0.647	0.000	0.553	0.647	0.740	0.647	0.353	0.353
F9	0.447	0.540	0.733	0.827	0.827	0.840	0.840	0.933	0.000	0.933	0.840	1.027	0.447	0.353
F10	0.590	0.683	0.683	0.683	0.590	0.504	0.504	0.704	0.883	0.000	0.969	0.969	0.876	0.676
F11	0.612	0.970	0.970	0.877	0.970	0.698	0.698	0.897	1.077	0.983	0.000	0.897	0.804	0.518
F12	0.472	0.565	0.472	0.472	0.852	0.758	0.633	0.727	0.440	0.503	0.472	0.000	0.597	0.503
F13	0.518	0.783	0.604	0.877	0.604	0.698	0.804	0.991	1.077	1.170	1.170	1.170	0.000	0.897
F14	0.877	0.791	0.612	0.518	0.604	0.698	0.612	0.718	0.812	1.170	1.077	0.983	1.077	0.000

Table 9. Normalized Direct-relation Matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
F1	0.000	0.051	0.064	0.039	0.075	0.039	0.033	0.042	0.034	0.028	0.052	0.049	0.058	0.057
F2	0.031	0.000	0.039	0.039	0.039	0.039	0.065	0.057	0.090	0.090	0.074	0.065	0.082	0.057
F3	0.055	0.050	0.000	0.069	0.077	0.049	0.047	0.042	0.047	0.061	0.061	0.086	0.058	0.066
F4	0.038	0.051	0.054	0.000	0.062	0.059	0.049	0.058	0.049	0.047	0.062	0.046	0.057	0.065
F5	0.065	0.031	0.048	0.073	0.000	0.057	0.065	0.074	0.090	0.073	0.065	0.048	0.039	0.039
F6	0.047	0.052	0.044	0.039	0.026	0.000	0.034	0.039	0.039	0.056	0.064	0.069	0.061	0.061
F7	0.084	0.076	0.084	0.084	0.050	0.050	0.000	0.024	0.033	0.066	0.058	0.058	0.059	0.050
F8	0.048	0.031	0.082	0.082	0.090	0.090	0.057	0.000	0.049	0.057	0.065	0.057	0.031	0.031
F9	0.039	0.048	0.065	0.073	0.073	0.074	0.074	0.082	0.000	0.082	0.074	0.090	0.039	0.031
F10	0.052	0.060	0.060	0.060	0.052	0.044	0.044	0.062	0.078	0.000	0.085	0.085	0.077	0.059
F11	0.054	0.085	0.085	0.077	0.085	0.061	0.061	0.079	0.095	0.087	0.000	0.079	0.071	0.046
F12	0.042	0.050	0.042	0.042	0.075	0.067	0.056	0.064	0.039	0.044	0.042	0.000	0.053	0.044
F13	0.046	0.069	0.053	0.077	0.053	0.061	0.071	0.087	0.095	0.103	0.103	0.103	0.000	0.079
F14	0.077	0.070	0.054	0.046	0.053	0.061	0.054	0.063	0.071	0.103	0.095	0.087	0.095	0.000

From the results reported in Table 10, one may note that adaptability to change (F11) emerges as the most prominent facilitator, followed by regulatory support (F13), leadership support (F10), training and education (F9), and collaboration and partnerships (F14). These top facilitators reflect the multifaceted challenges in healthcare technology adoption, as Agarwal et al. (2010) and Peek et al. (2020) highlighted. Interestingly, technological factors such as immersive tech interactivity with pain management (F1), user-friendliness (F6), and data security and privacy (F7) ranked lower in prominence, contrasting with the emphasis on technological features in some previous studies (Eckert et al., 2019; Yeung et al., 2021) and suggesting a shift in priorities when adopting immersive technologies in healthcare. This contrast may be due to evolving healthcare priorities, increased technological maturity, changing user expectations and behavior as healthcare organizations become more digital, and barriers to adoption shifting from technological concerns toward factors that enable effective integration into existing workflows and institutional structures. The net effect scores categorize facilitators as either cause or effect groups. Cause facilitators, with positive net effect scores, exert more impact on other facilitators than they receive, while effect facilitators, with negative net effect scores, are more impacted by others. Figure 2 visualizes this distribution, revealing that regulatory support (F13) is among the most effective facilitators, showing a high positive net effect and strong correlation. This suggests that while these facilitators are crucial, they are heavily influenced by other factors in the adoption process, aligned with observations by Thomson (2023) and Chang et al. (2007). It is also to be noted that once the cause group facilitators are taken care of,

other facilitators get automatically settled to a certain extent, as these are the outputs of the influence of the cause group. It helps the managers prioritize the facilitators requiring immediate attention.

Table 10. Total Relation Matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	Pi
F1	0.147	0.205	0.228	0.212	0.247	0.202	0.188	0.211	0.211	0.221	0.243	0.245	0.223	0.204	2.986
F2	0.212	0.196	0.247	0.255	0.257	0.243	0.255	0.266	0.304	0.325	0.310	0.309	0.285	0.238	3.704
F3	0.230	0.238	0.202	0.275	0.286	0.246	0.233	0.246	0.259	0.290	0.291	0.320	0.259	0.243	3.617
F4	0.201	0.225	0.239	0.195	0.256	0.240	0.221	0.244	0.245	0.261	0.275	0.266	0.242	0.228	3.335
F5	0.237	0.219	0.249	0.278	0.214	0.252	0.248	0.273	0.294	0.298	0.292	0.283	0.239	0.216	3.592
F6	0.194	0.211	0.213	0.214	0.206	0.167	0.192	0.211	0.218	0.250	0.257	0.268	0.230	0.210	3.043
F7	0.256	0.262	0.281	0.288	0.262	0.245	0.188	0.230	0.246	0.295	0.289	0.295	0.261	0.231	3.629
F8	0.221	0.217	0.277	0.284	0.295	0.280	0.238	0.201	0.255	0.281	0.290	0.289	0.230	0.209	3.568
F9	0.230	0.251	0.281	0.297	0.300	0.285	0.272	0.298	0.229	0.326	0.320	0.342	0.257	0.225	3.913
F10	0.240	0.262	0.276	0.284	0.281	0.258	0.246	0.281	0.303	0.252	0.331	0.339	0.291	0.250	3.893
F11	0.271	0.314	0.331	0.334	0.345	0.305	0.292	0.329	0.353	0.369	0.290	0.372	0.318	0.268	4.491
F12	0.193	0.210	0.214	0.221	0.253	0.234	0.214	0.236	0.221	0.243	0.240	0.206	0.224	0.197	3.107
F13	0.274	0.312	0.315	0.345	0.329	0.317	0.311	0.348	0.365	0.397	0.397	0.407	0.264	0.306	4.687
F14	0.287	0.297	0.297	0.299	0.310	0.299	0.279	0.310	0.327	0.378	0.371	0.373	0.335	0.219	4.381
Sj	3.194	3.421	3.649	3.780	3.841	3.574	3.376	3.685	3.830	4.184	4.193	4.314	3.659	3.245	

Table 11. Prominence (Importance) and Net Effect (causal) of the Facilitators

GROUP (DOI AND TOE)	Facilitators	Facilitators name	P	S	P-S	P+S	Prominence rank (P+S)
Relative advantage	F1	Immersive tech interactivity with Pain Management	2.986	3.194	-0.207	6.180	14
	F2	Precision Surgical Guidance	3.704	3.421	0.283	7.125	10
	F3	Cognitive Wellness Sculpture	3.617	3.649	-0.032	7.266	8
Compatibility	F4	Interoperability with existing systems	3.335	3.780	-0.445	7.115	11
	F5	EHR-compatible AR/VR solutions	3.592	3.841	-0.249	7.433	6
Complexity	F6	User-friendliness	3.043	3.574	-0.532	6.617	13
	F7	Data security and privacy	3.629	3.376	0.253	7.005	12
Organization	F8	Technology Readiness	3.568	3.685	-0.117	7.252	9
	F9	Training and education	3.913	3.830	0.083	7.744	4
	F10	Leadership support	3.893	4.184	-0.291	8.077	3
	F11	Adaptability to change	4.491	4.193	0.297	8.684	1
	F12	Evaluation and feedback	3.107	4.314	-1.207	7.421	7
External TASK ENVIRONMENT	F13	Regulatory support (Government support | Government involvement)	4.687	3.659	1.028	8.345	2
	F14	Collaboration and partnerships	4.381	3.245	1.136	7.625	5

6.3.1 Ranking Facilitator Groups by Prominence

Table 12 presents the average prominence scores for each group of facilitators identified in the theoretical model. These groups are ranked based on their average scores, providing insights into their relative influence on adopting immersive technologies. Table 12 shows that the External Task Environment group (7.985) has the highest average prominence score, suggesting that factors external to the healthcare organization, such as regulatory support (government support), play a crucial role in driving adoption. This aligns with findings from previous studies that emphasize the importance of external factors in healthcare technology adoption (Agarwal et al., 2010; Peek et al., 2020). This is followed by the Organization group (7.8356), highlighting the importance of internal organizational factors like leadership support, cultural readiness, and resource allocation for successful implementation. The high prominence of organizational factors is consistent with research by Chau & Hu (2002) and Gagnon et al. (2016), who found that organizational context significantly influences healthcare professionals' technology adoption decisions. The Compatibility group (7.274) emphasizes the significance of ensuring compatibility between immersive technologies and existing healthcare infrastructure (e.g., EHR systems) to minimize disruption. This finding supports the work of Villarreal et al. (2023), who identified interoperability as a critical factor in healthcare technology adoption. The Relative Advantage group (6.857) underscores the importance of demonstrating the clear benefits of immersive technologies compared to existing practices to gain stakeholder buy-in. This is consistent with Rogers' (2010) Diffusion of Innovation theory, which posits that perceived relative advantage is a key driver of innovation adoption. Finally, the Complexity group (6.811) suggests that the inherent complexity of immersive technologies should be addressed through training and user-friendly design to facilitate adoption. This aligns with findings from Mäkinen et al. (2022), who emphasized the importance of user-friendliness in healthcare technology adoption.

Table 12. Prominence and Net Effect of the Group of Facilitators

FACILITATORS	AVERAGE PROMINENCE
RELATIVE ADVANTAGE	6.857
COMPATIBILITY	7.274
COMPLEXITY	6.811
ORGANIZATION	7.8356
EXTERNAL TASK ENVIRONMENT	7.985

6.3.2 Prominence and Relationships Between Facilitators

This study positions itself within the literature stream of healthcare technology adoption, focusing specifically on the adoption of immersive technologies in emerging economy healthcare contexts through the integrated lens of the Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory. This literature stream examines how complex healthcare organizations evaluate, adopt, and implement innovative technologies within their unique contexts. Prior research in this area has often emphasized technological factors in adoption decisions (Eckert et al., 2019; Yeung et al., 2021), but our findings suggest a more nuanced perspective is necessary, particularly when examining resource-constrained healthcare environments.

The interrelationships among facilitators reveal a complex adoption landscape for immersive technologies in healthcare. Using the prominence scores (P+S) from Table 11, identified the top five prominent facilitators of immersive technology in the Indian healthcare system. Ensuring adaptability to change (F11) is crucial for navigating the potentially disruptive nature of these technologies. This finding is consistent with Alkraiji et al. (2013), who identified organizational flexibility as a key factor in health information technology adoption. Kneebone et al.'s (2010) concept of "distributed simulation" aligns with India's healthcare landscape, where immersive technologies must function across varied settings. This approach delivers "accessible immersive training" that can be deployed wherever needed, which is crucial in a country where rural facilities struggle with what Yang et al. (2022) describe as 'low equipment coverage' and "low technological competence". Adaptable immersive solutions could enhance the effectiveness of frontline healthcare workers, including community health workers who provide primary care in marginalized communities with limited access to advanced training facilities.

Securing strong regulatory support (F13) and leadership support (F10) is essential for overcoming potential roadblocks and fostering widespread adoption. The importance of regulatory and leadership support aligns with findings from Chang et al. (2007) and Thomson (2023), who emphasized the role of these factors in healthcare technology implementation. Bhattacharya et al. (2022) highlight the regulatory framework for immersive technologies in the Indian context through the "Ayushman Bharat Digital Mission (ABDM)" which aims to develop "a national digital health ecosystem that is effective, affordable, accessible, inclusive, safe, and supports universal health coverage." This initiative creates the regulatory structure within which immersive technologies must operate to address healthcare challenges including what Yang et al. (2022) identify as issues with equipment coverage, technological competence, and patient satisfaction.

Investing in training and education (F9) equips healthcare professionals with the necessary skills to leverage these new technologies effectively. This corroborates the findings of Gutierrez-Bucheli et al. (2024) and Liu et al. (2021), who highlighted the critical role of training in technology adoption in healthcare settings. Lemée et al. (2024) demonstrate that immersive virtual reality develops "various skills, and clinical judgment" even in rural settings with limited infrastructure. This finding has implications for India's healthcare workforce challenges, particularly in addressing what Bhattacharya et al. (2022) describe as "insufficient and poor medical training and learning methods." Immersive technologies could transform healthcare education by offering what Kim et al. (2023) describe as "interactive training of healthcare workers" and Karbasi and Kalhori, (2020) state about "anatomical training for medical students" through virtual environments.

Collaboration and partnerships (F14) from the external task environment group are also highly prominent. This aligns with research by Brown et al. (2010) and Cook et al. (2019), who found that inter-organizational collaborations facilitate technology adoption in healthcare settings. The importance of partnerships is evident in India, where Bhattacharya et al. (2022) report that institutions like "Apollo Hospitals collaborates with 8chili Inc to enter the Metaverse" and "AIIMS, New Delhi implemented new digital surgery technology from Immersive Touch." These partnerships address what Yang et al. (2022) identify as limitations that "prevent contact between Cloud Experts and Terminal Doctors." They represent practical implementations of what Ebbert et al. (2023) describe as collaborative models between traditional and digital providers - crucial for implementing immersive technologies across India's diverse healthcare delivery system.

An in-depth examination of the total relation matrix in Table 10 and Figure 2 offers a complete understanding of how these facilitators interact within the healthcare system's immersive technology framework. Given the broad scope of facilitators studied, focus on identifying significant relationships in the total relation matrix to address our second research question (RQ2). Utilizing a threshold to highlight the most meaningful relationships among factors is standard practice in DEMATEL studies, as referred to in section 5.3 (Singh et al., 2024; Fu et al., 2012). Data in Table 13 shows that adaptability to change (F11) is significantly influenced by regulatory support (F13), collaboration and partnerships (F14), training and education (F9), and leadership support (F10). This complex interplay of factors supports the findings of Agarwal et al. (2010) and Peek et al. (2020), who emphasized the multifaceted nature of healthcare technology adoption. This suggests that an organization's ability to adapt to immersive technologies depends on appropriate conditions for their use, including a supportive regulatory framework, operational standards, and governance rules. In turn, F11 significantly enhances precision surgical guidance (F2), cognitive wellness sculpture (F3), EHR-compatible AR/VR solutions (F5), technology readiness (F8), training and education (F9), leadership support (F10), and evaluation and feedback (F12). For instance, regulatory support can create an environment conducive to change, while effective training programs can equip healthcare professionals with the skills needed to adapt to new technologies. Leadership, in turn, can drive the organizational culture necessary for embracing change.

Regulatory support (F13), the second most prominent facilitator, is significantly influenced by collaboration and partnerships (F14). F13 significantly enhances interoperability with existing systems (F4), EHR-compatible AR/VR solutions (F5), user-friendliness (F6), data security and privacy (F7), technology readiness (F8), training and education (F9), leadership support (F10), adaptability to change (F11), and evaluation and feedback (F12). This wide-ranging influence of regulatory support aligns with the findings of Yang et al. (2015), who identified government policy as a critical factor in healthcare technology adoption. Kim et al. (2023) emphasize that successful implementation of immersive technologies requires addressing "privacy protection, data safeguarding, and innovation in artificial intelligence." These regulatory considerations are relevant to India's digital health transformation, where the ABDM must ensure health information is "safe, private, and confidential" (Bhattacharya et al., 2022) while promoting innovation. The significant influence of regulatory support on multiple facilitators reflects implementation challenges where Yang et al. (2022) note that "the limits of Internet technology" currently prevent optimal clinical collaboration through immersive environments.

Leadership support (F10), the third most prominent facilitator, acts as a central point in the system. It is an effect facilitator mainly influenced by precision surgical guidance (F2), training and education (F9), adaptability to change (F11), regulatory support (F13), and collaboration and partnerships (F14). In turn, leadership support (F10) significantly contributes to enhancing adaptability to change (F11) and evaluation and feedback (F12). This central role of leadership support is consistent with the findings of Thong (1999) and Pears et al. (2020), who emphasized the critical role of top management support in technology adoption. Ebbert et al. (2023) highlight how leadership is essential for developing collaborative models where "traditional and digital health care providers" complement each other's strengths. This leadership approach has relevance in India, where Bhattacharya et al. (2022) discuss collaborations between hospitals, government agencies, and technology companies to implement immersive technologies. Such partnerships require leadership that can transform theoretical concepts into practical implementations that connect specialty care centers with primary care facilities through virtual environments.

Training and education (F9), the fourth most prominent facilitator, is significantly influenced by adaptability to change (F11), regulatory support (F13), and collaboration and partnerships (F14). F9 significantly enhances leadership support (F10), adaptability to change (F11), and evaluation and feedback (F12). This finding aligns with the work of Gutierrez-Bucheli et al. (2024) and Liu et al. (2021), who highlighted the importance of comprehensive training programs in healthcare technology adoption. Lemée et al. (2024) provide practical insights into immersive technology training, finding that challenges such as "cognitive overload, cyber sickness and stress" can be mitigated through "good briefing/debriefing, familiarization time, and gradation in the intensity of cases". These considerations are important in India's multi-tiered healthcare workforce, where Yang et al. (2022) identify the need for "graded diagnosis and treatment" processes that connect expertise across boundaries. Immersive training could benefit healthcare workers at all levels by enabling what Bhattacharya et al. (2022) describes as "tactile haptic controls" for surgical training and "interactive training materials that improve understanding of fundamental principles".

Collaboration and partnerships (F14), ranked fifth in prominence, significantly enhance technology readiness (F8), training and education (F9), leadership support (F10), adaptability to change (F11), evaluation and feedback (F12), and regulatory support (F13). This wide-ranging influence of collaborations and partnerships supports the findings of Brown et al. (2010) and Cook et al. (2019), who identified inter-organizational relationships as key drivers of technology adoption in healthcare settings. Kneebone et al. (2010) highlight how partnerships enable "high-fidelity immersive simulation" to be widely available. This collaborative approach addresses India's healthcare challenges, where Bhattacharya et al. (2022) identify immersive technologies' potential to overcome registration problems and enable the "Medical Internet of Things" for improved diagnostics. The Indian healthcare sector has begun implementing such partnerships, with organizations creating what Bhattacharya et al. (2022) describe as "virtual hospital" settings that demonstrate the value of collaboration in implementing immersive technologies.

These findings hold particular significance in the context of the Indian healthcare system. The high prominence of regulatory support reflects the complex regulatory environment of India's healthcare sector, characterized by multiple overlapping authorities and evolving digital health policies. The regulatory framework may address significant infrastructure and access disparities in a country where 65% of the 1.4 billion population resides in rural areas. Similarly, leadership support's importance aligns with the hierarchical organizational structure prevalent in Indian healthcare institutions, where top-down decision-making remains the dominant model. The emphasis on training and education directly addresses India's specific challenges in healthcare workforce development and digital literacy, which are particularly acute in smaller cities and rural areas. The role of collaboration and partnerships becomes especially crucial given India's diverse healthcare delivery system spanning public, private, and non-governmental sectors, often operating with limited coordination mechanisms.

A particularly notable finding is the causal relationship between regulatory support (F13) and organizational factors including adaptability to change (F11), leadership support (F10), and training and education (F9). This pattern suggests that external environmental factors significantly shape internal organizational readiness for immersive technology adoption. Furthermore, the relatively low prominence of technological factors like user-friendliness (F6) and data security (F7) indicates that while these factors remain important, they are insufficient drivers of adoption without the support of organizational and environmental facilitators.

These interrelationships demonstrate that immersive technology adoption in healthcare is not a linear process but a complex system of interacting factors. The prominence of organizational and environmental factors over technological ones suggests a shift in focus from the technology itself to the ecosystem supporting its adoption. This finding aligns with recent research by Dwivedi et al. (2022) and Agarwal et al. (2010), who emphasize the importance of considering the broader socio-technical context in healthcare technology adoption.

The cross-boundary coordination required for immersive technology adoption becomes evident through our analysis of facilitator relationships. Cross-boundary coordination refers to activities that span organizational boundaries to exchange information and coordinate actions with external stakeholders. Our findings highlight how healthcare organizations must effectively manage relationships across multiple domains, including interactions between healthcare providers and technology vendors, regulatory bodies and operational units, and public and private healthcare sectors. This cross-boundary perspective explains the prominence of collaboration and partnerships (F14) in our results.

Interestingly, our findings reveal that purely technological factors such as immersive tech interactivity with pain management (F1), user-friendliness (F6), and data security and privacy (F7) ranked lower in prominence. This contrasts with some earlier studies that emphasized technological features as primary drivers of adoption (Eckert et al., 2019; Yeung et al., 2021). Our results suggest that in the context of immersive technologies in healthcare, organizational and environmental factors may play a more crucial role than technological features alone. This shift in focus aligns with more recent literature that emphasizes the importance of organizational readiness and supportive ecosystems in healthcare technology adoption (e.g., Peek et al., 2020; Thomson, 2023).

Healthcare institutions may develop effective strategies for adopting immersive technologies by understanding these interconnections. For instance, efforts to enhance adaptability to change should be coupled with initiatives to secure regulatory support and develop strong leadership. Similarly, training programs should be designed not just to impart technical skills, but also to foster a culture of innovation and change readiness.

This study provides an insightful summary of the findings. First, despite the highly technical nature of immersive technologies, technological factors were consistently outranked by organizational and environmental factors in their influence on adoption. Second, the study reveals the central role of adaptability to change as the most prominent facilitator, suggesting that cultural and organizational flexibility may be more important than technological sophistication. Third, while data security and privacy concerns are often highlighted as major barriers in healthcare technology literature, these factors ranked surprisingly low in our analysis. Fourth, the study demonstrates the significant influence of external task environment factors, particularly regulatory support and collaboration, challenging the notion that adoption decisions are primarily driven by internal organizational factors. Finally, the complex interrelationships among facilitators reveal that successful adoption requires a coordinated approach addressing multiple factors simultaneously rather than isolated interventions focused on individual facilitators.

Table 13. Significant Relation Coefficients Between Influenced and Influencing Facilitators

		INFLUENCED FACILITATORS										
		F2	F3	F4	F5	F6	F8	F9	F10	F11	F12	F13
INFLUENCING FACILITATORS	F2								0.325			
	F3										0.32	
	F9								0.326	0.32	0.342	
	F10									0.331	0.339	
	F11	0.314	0.331		0.345		0.329	0.353	0.369		0.372	
	F13			0.345	0.329	0.317	0.348	0.365	0.397	0.397	0.407	
	F14						0.31	0.327	0.378	0.371	0.373	0.335

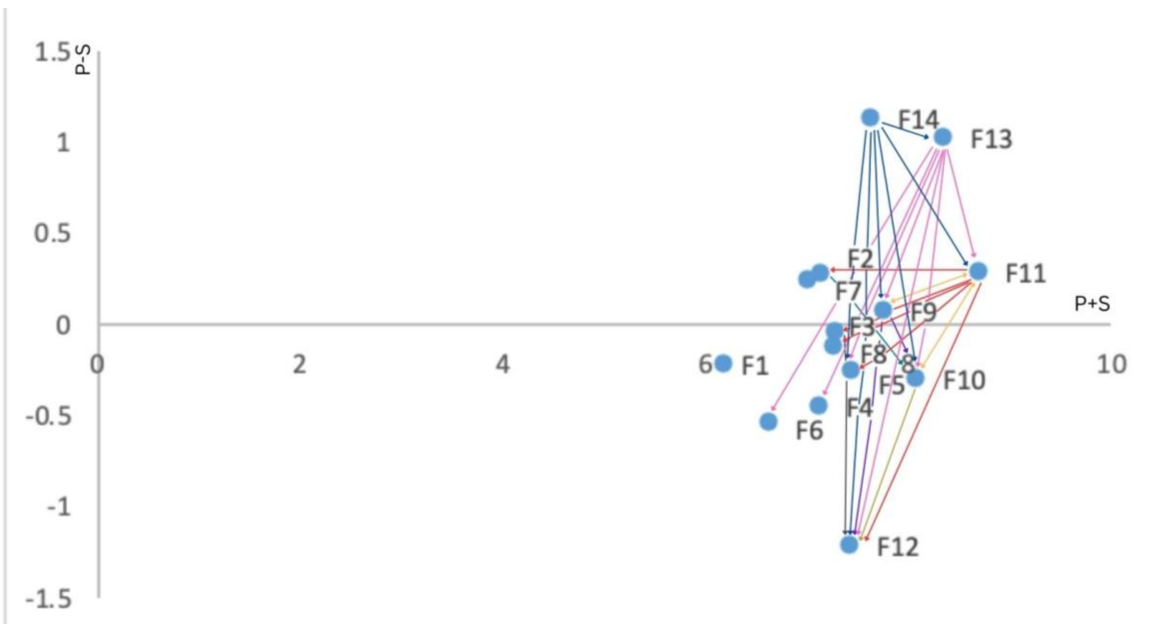

Figure 2. Prominence and Net Effect Diagram

Our findings on the prominence of adaptability to change and regulatory support as key facilitators underscore the importance of contextual factors in shaping technology adoption, as emphasized by the TOE framework. Furthermore, the complex interrelationships revealed by our analysis highlight how multiple facilitators interact to collectively influence adoption decisions, supporting the multifaceted nature of innovation diffusion as proposed by DOI theory. This integrated perspective offers valuable insights for healthcare administrators and policymakers in India, who must address multiple interconnected factors simultaneously when implementing immersive technologies.

7 Sensitivity Analysis

To assess the robustness of our findings on facilitator prominence, conducted a comprehensive sensitivity analysis by varying expert weights across three scenarios, as shown in Table 5. This analysis aimed to determine if individual expert biases significantly affected facilitator prominence rankings. Three sensitivity tests with different weight distributions: the main results using original weightings, Sensitivity Analysis 1 adjusting weights of Experts 1 and 2, Sensitivity Analysis 2 modifying weights of Experts 1, 2, and 3, and Sensitivity Analysis 3 altering weights of Experts 1 and 4. Figure 3 visually represents these findings, illustrating consistent ranking patterns and proportional score increases across sensitivity analyses. The analysis revealed consistent patterns across scenarios. F11 (Adaptability to change), F13 (Regulatory support), and F10 (Leadership support) consistently remained the top three facilitators, with their prominence scores increasing proportionally, preserving relative importance. Mid-range facilitators like F9 (Training and Education), F5 (EHR-compatible AR/VR solutions), and F8 (Technology Readiness) maintained stable positions. Lower-ranked facilitators, such as F1 (Immersive tech interactivity with Pain Management) and F6 (User-friendliness), consistently remained at the bottom. While absolute prominence scores increased across analyses, relative differences between facilitators remained largely consistent. The general order of facilitator prominence is preserved across scenarios, with only minor shifts in relative positions. This proportional increase and ranking stability suggest that the overall structure of facilitator importance is robust to changes in expert weightings. This sensitivity analysis demonstrates that our findings on facilitator prominence are robust to variations in expert weightings. The stability in rankings across different scenarios enhances the practical applicability of our results in guiding immersive technology adoption in healthcare settings. It provides confidence that the identified facilitators and their relative importance remain valid under various expert opinion configurations, strengthening the reliability of our recommendations for healthcare organizations and policymakers.

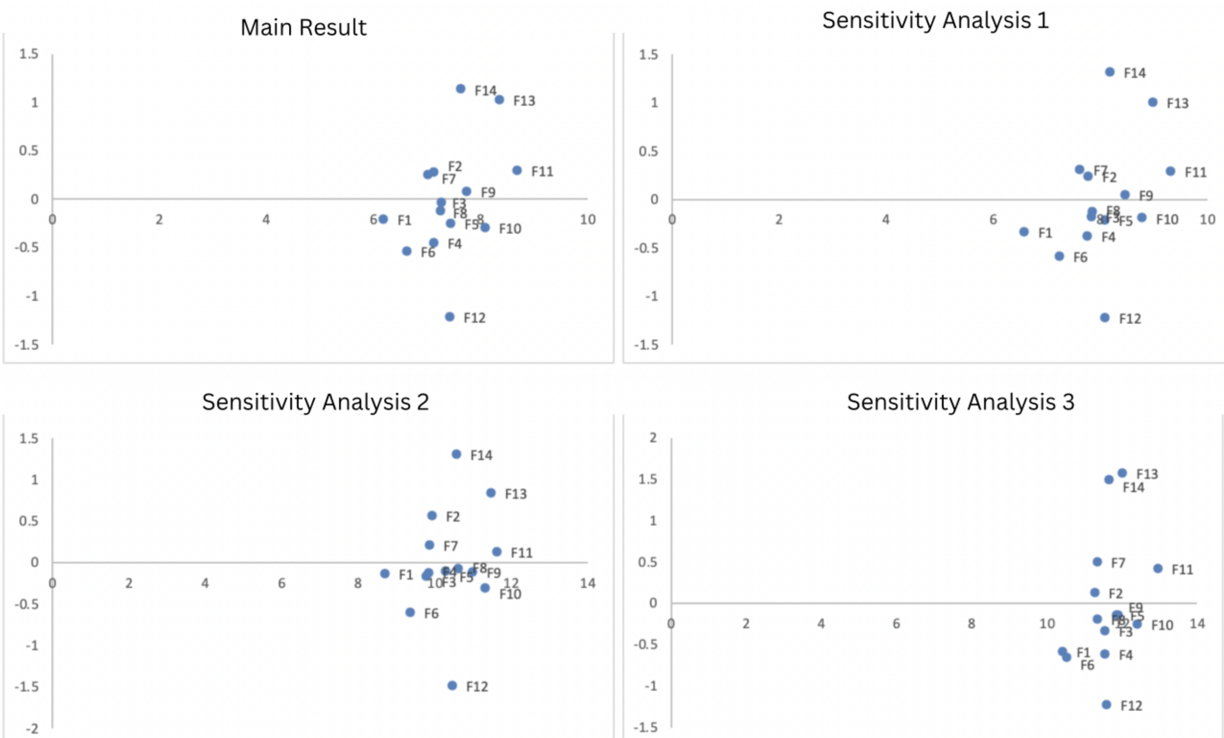

Figure 3. Prominence and Net Effect Diagram (Main Results and Sensitivity Analysis (1-3))

8 Theoretical Implication

This study significantly contributes to the literature on immersive technology adoption in healthcare contexts, particularly in emerging economies. By examining the Indian healthcare system through the integrated lens of the Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory, this research advances understanding of the contextual factors that influence adoption decisions in complex healthcare environments.

The primary theoretical contribution lies in extending the literature on healthcare technology adoption by demonstrating how the relative importance of adoption facilitators varies in the specific context of immersive technologies in emerging economy healthcare systems. While previous research has identified various factors influencing healthcare technology adoption (Chau & Hu, 2002; Gagnon et al., 2016), our study reveals the distinctive pattern of influences for immersive technologies, where organizational and environmental factors significantly outweigh technological factors. This finding extends the work of Eckert et al. (2019) and Yeung et al. (2021), who highlighted technological features as primary adoption drivers, demonstrating that organizational factors (adaptability to change) and environmental factors (regulatory support) serve as more important determinants in resource-constrained healthcare environments.

The study enhances understanding of cross-boundary coordination in healthcare innovation by highlighting the critical role of inter-organizational interactions in immersive technology adoption. The prominence of collaboration and partnerships in these findings demonstrate how adoption requires coordination across organizational boundaries. This extends previous work on healthcare innovation networks by illustrating the specific cross-boundary mechanisms that facilitate immersive technology adoption in resource-constrained healthcare environments.

9 Managerial Implication

This study offers several actionable insights for healthcare administrators and policymakers seeking to implement immersive technologies effectively. The findings highlight that a comprehensive approach addressing organizational, environmental, and technological factors simultaneously is essential for successful adoption. Based on the prominence and interrelationships of facilitators, propose specific strategic interventions for key stakeholders in the Indian healthcare ecosystem.

For healthcare administrators, the high prominence of adaptability to change indicates the critical importance of developing an innovation-oriented organizational culture. Healthcare organizations should implement structured change management programs that focus on both technological infrastructure and human resource readiness. This involves establishing innovation champions within different departments, creating safe spaces for experimentation with immersive technologies, and developing metrics to track organizational flexibility. Additionally, the strong relationship between adaptability to change and training programs suggests that healthcare organizations should invest in continuous professional development that builds both technical skills and adaptability capabilities simultaneously rather than addressing them separately. For policymakers, the significant influence of regulatory support highlights the need for developing clear policy frameworks that facilitate rather than hinder immersive technology adoption. In the Indian context, where healthcare is regulated by multiple authorities at central and state levels, policy coherence is particularly important. Regulatory initiatives should address interoperability standards, data privacy concerns specific to immersive technologies, and reimbursement models for virtual care delivery. The Government of India's National Digital Health Mission provides a foundation. Still, specific provisions for immersive technologies need to be developed in consultation with healthcare providers, technology developers, and patient representatives. For technology developers and vendors, the findings regarding interoperability with existing systems and EHR-compatible AR/VR solutions highlight the importance of designing immersive technologies that integrate seamlessly with India's evolving digital health infrastructure. Rather than developing standalone solutions, vendors should focus on creating platforms compatible with existing health information systems. The relatively lower prominence of user-friendliness does not diminish its importance but suggests that it should be considered in conjunction with broader organizational and environmental factors rather than in isolation. For educational institutions and professional associations, the high prominence of training and education highlights their crucial role in preparing healthcare professionals for immersive technology adoption. Medical and allied health professional education in India should incorporate immersive technology training in their curricula while continuing education programs should provide upskilling opportunities for practicing professionals. Professional bodies can develop competency frameworks and certification programs specific to immersive technology applications in healthcare. The findings also highlight the value of multi-stakeholder collaboration, as evidenced by the high prominence of collaboration and partnerships. The Indian healthcare sector should develop structured platforms for public-private partnerships focused explicitly on immersive technology adoption. Industry associations, academic institutions, healthcare providers, and government agencies should establish collaborative innovation centers to share knowledge, resources, and best practices.

10 Conclusion

Immersive technology in healthcare can be described as a radical shift that promises to change how services are delivered, how people are educated and trained, and how patients are treated. This study has offered an account of the factors that influence the use of these technologies in India's healthcare sector, and it holds implications for both theory and practice. This study, using the Technology-Organization-Environment (TOE) model and Diffusion of Innovation (DOI) theory, assessed by the Grey-

DEMATEL method, shows that adoption facilitators are initiated from organizational and environmental aspects, proportionately more than the merely technical elements. They identified the enhanced important facilitators like adaptability to change, regulatory support, and leadership commitment. This makes a new strategy aimed at a technology-centered approach inadequate because the nature of integrated healthcare technology is diverse and context-sensitive. It is significant for advancing a theoretical framework for accepting technology in complex organizations and providing valuable recommendations to healthcare managers, policymakers, and developers of advanced technologies.

Furthermore, the study's findings highlight that organizational culture, regulatory environment, and leadership commitment are vital components in successfully implementing immersive technologies in the health sector. Such findings demonstrate the role of these factors as critical components of a complex system and emphasize the importance of a multifaceted approach based on interventions within the technological, organizational, and environmental domains simultaneously. As immersion technologies provide more options for improving the organization of the healthcare industry, this study may help healthcare institutions understand and manage the risks and benefits associated with using new technologies.

However, it is important to recognize that while this study focused on the Indian healthcare context, the applicability of its findings to other healthcare systems and cultural contexts requires further investigation. Future research could explore how the importance of different facilitators may vary across different types of immersive technologies, healthcare experts, or geographical regions. Future research may apply the Grey-DEMATEL methodology to compare facilitator importance across different healthcare systems and track how these relationships evolve as immersive technologies mature in various cultural, economic, and regulatory environments. Additionally, longitudinal studies could provide valuable insights into how the relative importance of these facilitators changes over time as immersive technologies become more established in healthcare settings. Ultimately, realizing the transformative potential of immersive technologies in healthcare requires a concerted effort from healthcare providers, policymakers, and technology developers to create an environment that fosters innovation while ensuring patient safety and quality of care. Understanding the main facilitators presented in this study and using them as a foundation may help healthcare organizations become more prepared to successfully implement and enhance immersive technologies, which in turn has implications for optimizing patient care pathways and improving medical education and training.

Declaration of AI

In the preparation of this paper, OpenAI's ChatGPT was employed to assist in drafting the discussion section. The AI-generated content was then thoroughly reviewed and refined by the author(s) to ensure it accurately reflected our research objectives and maintained coherence.

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Appendix A: Direct-Relation Matrix for Expert 2

Facilitator	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
F1: Immersive tech interactivity with Pain Management	0	3	2	3	4	3	3	4	3	3	4	4	4	4
F2: Precision Surgical Guidance	3	0	3	3	3	3	3	4	4	4	4	3	4	4
F3: Cognitive Wellness Sculpture	3	3	0	2	4	2	3	3	3	4	2	4	4	4
F4: Interoperability with existing systems	3	2	3	0	3	2	4	4	4	3	3	3	4	4
F5: EHR-compatible AR/VR solutions	3	3	3	3	0	4	4	4	4	3	3	3	3	3
F6: User-friendliness	2	2	2	2	3	0	3	3	3	4	4	4	4	4
F7: Data security and privacy	3	3	3	3	3	3	0	2	2	2	2	2	3	3
F8: Technology Readiness	3	3	4	4	4	4	4	0	4	4	4	4	3	3
F9: Training and education	3	3	3	3	3	4	4	4	0	4	4	4	3	3
F10: Leadership support	3	3	3	3	3	3	3	4	4	0	4	4	4	3
F11: Adaptability to change	3	3	3	3	3	3	3	4	4	4	0	4	4	3
F12: Evaluation and feedback	3	3	3	3	3	3	2	2	2	4	3	0	4	4
F13: Regulatory support	3	3	3	3	3	3	4	4	4	4	4	4	0	4
F14: Collaboration and partnerships	3	3	3	3	3	3	3	4	4	4	4	4	4	0

Appendix B: Direct-Relation Matrix for Expert 3

Facilitator	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
F1: Immersive tech interactivity with Pain Management	0	1	2	1	2	1	0	2	1	1	2	3	1	0
F2: Precision Surgical Guidance	1	0	2	1	2	1	1	1	2	2	1	2	2	1
F3: Cognitive Wellness Sculpture	2	1	0	2	0	3	2	1	2	1	2	1	2	2
F4: Interoperability with existing systems	1	2	1	0	2	2	1	2	1	2	2	1	1	2
F5: EHR-compatible AR/VR solutions	1	1	2	2	0	1	2	1	2	2	1	2	2	1
F6: User-friendliness	2	3	3	2	1	0	1	2	2	1	1	2	2	2
F7: Data security and privacy	2	1	2	2	1	2	0	1	2	2	1	1	2	1
F8: Technology Readiness	2	1	1	1	2	2	2	0	1	1	2	2	1	1
F9: Training and education	1	2	1	2	2	1	1	2	0	2	1	2	2	1
F10: Leadership support	1	2	2	2	1	2	2	2	2	0	2	2	1	1
F11: Adaptability to change	2	2	2	1	2	1	2	1	2	1	0	1	1	2
F12: Evaluation and feedback	1	2	1	1	2	1	1	2	2	1	2	0	2	1
F13: Regulatory support	2	1	1	2	1	2	1	2	1	2	2	2	0	1
F14: Collaboration and partnerships	1	2	2	1	1	2	2	1	2	2	2	1	2	0

Appendix C: Direct-Relation Matrix for Expert 4

Facilitator	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
F1: Immersive tech interactivity with Pain Management	0	2	3	2	3	2	3	2	3	2	3	2	3	3
F2: Precision Surgical Guidance	2	0	2	3	2	3	3	3	3	3	2	2	2	3
F3: Cognitive Wellness Sculpture	3	3	0	3	2	3	2	2	2	3	2	3	2	3
F4: Interoperability with existing systems	3	3	3	0	3	2	3	3	3	3	3	2	2	2
F5: EHR-compatible AR/VR solutions	3	2	3	3	0	3	3	2	3	3	3	3	2	3
F6: User-friendliness	3	3	2	2	2	0	3	3	3	2	3	3	2	2
F7: Data security and privacy	3	3	3	3	3	2	0	2	2	3	3	3	3	3
F8: Technology Readiness	3	2	3	3	3	3	2	0	2	3	3	2	2	2
F9: Training and education	3	3	3	3	3	2	2	2	0	2	2	3	2	2
F10: Leadership support	3	3	3	3	3	3	3	3	3	0	2	2	2	2
F11: Adaptability to change	3	3	3	3	3	3	2	3	2	2	0	3	2	2
F12: Evaluation and feedback	3	3	3	3	3	3	3	3	3	2	2	0	2	2
F13: Regulatory support	2	2	2	2	2	2	2	3	3	3	3	3	0	3
F14: Collaboration and partnerships	3	3	3	3	2	2	3	3	3	3	2	2	2	0

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