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RESEARCH

Enhancing Flexible Healthcare Management Through the Adoption of Digital Twin Technology: An Integrated UTAUT2-TOE Framework with SEM-ANN Analysis

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Abstract *This study examines the behavioral and organizational factors that influence the adoption of digital twin (DT) technologies in healthcare, particularly in resource-constrained environments such as Bangladesh. It emphasizes the often-overlooked human and institutional aspects of DT adoption, alongside technical considerations. An integrated model was developed by combining the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with the Technology-Organization-Environment (TOE) framework, drawing on six key constructs from each. Data collected from 439 healthcare professionals were analyzed using a hybrid approach of structural equation modeling (SEM) and artificial neural networks (ANNs). The results show that all predictors have a significant impact on behavioral intention, with complexity having a negative effect. ANN sensitivity analysis identified regulatory support, effort expectancy, facilitating conditions, and complexity as the most influential factors. These contribute to flexible management dimensions in hospitals. While the model explains 88.4% of the variance in behavioral intention, it accounts for only 8.5% of actual DT adoption, suggesting the influence of other organizational factors. This study is among the first to use an integrated UTAUT2-TOE framework with an SEM-ANN approach for DT adoption in healthcare. The findings provide valuable insights for healthcare policymakers, underscoring the importance of supportive infrastructure, user-friendly technology, and regulatory alignment.*

Keywords Behavioral intention · Digital twin adoption · Flexible healthcare · SEM-ANN model · UTAUT2-TOE framework

Introduction

The COVID-19 crisis has initiated a significant conversation around the need for flexible healthcare systems, particularly in settings where resources are limited (Tiwari et al., 2025; Turner, 2023). In these environments, access to healthcare can often be challenging due to inadequate infrastructure or funding (Essar et al., 2023). One promising approach to addressing these issues is through digital transformation (Alnoor et al., 2024; Garcia-Perez et al., 2023; Massaro, 2023). It is undeniable that the digital transformation cannot, in itself, overcome all the physical shortages and infrastructural shortcomings. Nevertheless, this transformation can help the managers and health practitioners to better utilize the existing resources. Thus, the functional capacity of limited infrastructure can be extended by leveraging digital transformation's data integration and monitoring abilities (Martínez-Peláez et al., 2023). This digital shift not only improves patient access to essential services but also helps streamline operations,

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making it a cost-effective strategy to enhance the overall flexibility of healthcare management. In the context of this study, flexible healthcare management refers to the overall system's ability to adapt to continuously changing patient demands and resource availability. From real-time resource allocation to cross-department coordination, everything falls under the responsibility of flexible management. The integration of digital technologies can help healthcare organizations to achieve and sustain this flexibility more effectively (Wang et al., 2021).

The healthcare sector is undergoing a fundamental shift toward digital transformation (Altman Ferreira, 2025). Digital health innovations such as electronic health records (EHRs) and telemedicine have already made the job of doctors and health practitioners easier (Adeniyi et al., 2024). EHRs and other current technologies are increasingly incorporating decision support functionalities for various clinical scenarios. These digital platforms are mainly designed for episodic documentation, which provides rule-based alerts (Attard Trevisan, 2025). So, these advanced systems are not focused on dynamically simulating evolving clinical conditions. On the other hand, Digital Twin (DT) technology is capable of creating and monitoring virtual replicas of patients and even clinical processes, which builds upon the data architecture established by EHR systems and introduces an advanced analytical and simulation layer over existing digital infrastructure (Awasthi et al., 2025). DT does this without replacing the existing digital tools and systems that are already in place, rather extends their capabilities toward dynamic and interactive decision making. A real-time interaction between data and decision making is now possible because of the analytical and predictive capabilities of DT. Such capabilities contribute directly to making the healthcare management system more flexible.

A DT is a real-time virtual representation of a physical entity such as a person, process, or system, achieved through continuous data integration (Daraio et al., 2025; Dihan et al., 2024; Tao et al., 2019). It accurately mirrors the actual entity, enabling it to deliver functional services and fulfill specific application requirements (Sedlack & Aamer, 2025; Tao et al., 2022). In healthcare, a DT represents computerized models of human organs, tissues, cells, or microenvironments that can predict outcomes for their real-life counterparts and evolve in response to new online data (Sun et al., 2023). The DT architecture is composed of various enabling technologies, including cloud computing, blockchain-based smart contracts, artificial intelligence, cyber-physical systems, and the Internet of Things (Hossain et al., 2025; Liu et al., 2021; Qi et al., 2021). Although DTs have been primarily associated with manufacturing in existing literature (Singh et al., 2021), their application in healthcare has enabled clinicians and researchers to gain deeper insights into disease progression, leading to more accurate diagnoses and more effective therapies (Sun et al., 2023). Hospitals have utilized digital twins to simulate surgical procedures to identify potential complications, optimize radiological workflows to reduce patient wait times, and continuously monitor patient health to detect risks at an early stage (Chauhan & Bahad, 2025; Zhang et al., 2020). Researchers have utilized DT technology to generate 3D X-ray images of healing bones (Aubert et al., 2021), develop a four-stage immune system model (Laubenbacher et al., 2022), and uncover new insights through data- and AI-driven anatomical analysis (Sun et al., 2023). According to Kaur et al. (2024), DT has also facilitated secure patient data management by leveraging blockchain technology and cloud computing. DT enhances patient care and operational efficiency by equipping decision-makers with tools for making strategic choices, particularly in resource-constrained and complex healthcare management environments. Bangladesh, as a developing country, faces challenges such as overcrowded and underfunded healthcare facilities (Patwary et al., 2022). Not only that, even with all the current digitalization, the hospitals in Bangladesh really struggle with patient flow management because their occupancy and emergency responses are not quite predictive. Additionally, the patients' data are not well integrated because each subsystem of the hospital is not connected. This leads to duplication of diagnostic tests and poor continuity of patient records. The implementation of DT can synchronize data across departments, optimize resource utilization, and monitor the clinical workflows in real time. However, implementing DT in Bangladesh may require context-specific strategies because of its resource-constrained environment. The management may consider doing a phased or modular adoption in healthcare, as implementing full-scale DT will require high computational infrastructure, a large number of skilled engineers, and significant investments (D. Wu et al., 2025). Adopting process-level twins in the beginning, such as dynamic patient flow or inter-department integration, can make full-scale DT implementation feasible. Furthermore, cloud-based platforms can substantially reduce the cost and even lower the technical barriers for DT adoption in low-income healthcare settings like Bangladesh (Waqar et al., 2023). Many other low- to middle-income countries (LMICs) are also investigating and trying to implement DT in several aspects of healthcare. For instance, Shrotri et al. (2025) analyzed the adoption factors for DT in oncology (Shrotri et al., 2025). They utilized TOE framework to structure these adoption factor and surveyed the healthcare stakeholders. de Oliveira Ribeiro et al. (2025) made a DT maturity model to understand whether the Brazilian hospitals are ready to adopt DT (de Oliveira Ribeiro et al., 2025). They conducted a literature review to uncover critical success factors for DT implementation and organized them into six conceptual classes. Thus, the global eagerness to implement DT in healthcare to make the system more efficient and resource-conscious is shared across multiple LMICs. In the case of LMICs, these studies suggest that this particular field is still moving toward full behavioral and institutional integration frameworks from conceptualizations of technical feasibility and maturity.

Various scholars have already explored various technology adoption in healthcare, such as healthcare professionals' readiness to adopt telemedicine (Schürmann et al., 2025), EHR adoption in low-income countries (Woldemariam & Jimma, 2023), and AI adoption in healthcare organizations (Kim et al., 2023). However, DT systems are not functionally competitive with these technologies. DT architectures create a synchronized cyber-physical framework by integrating and coordinating some digital components, such as AI-driven analytics, IoT-enabled monitoring, and EHR-based data infrastructures. Thus, DT is able to provide predictive decision making and organization-wide integration with continuous monitoring (Meijer et al., 2023). DT adoption will pose distinct challenges because a deeper organizational and cognitive alignment is required between the professionals, virtual environments, and the governing bodies. Thus, analyzing DT adoption will extend beyond just digital acceptance since we have to capture the organizational and behavioral capacities needed to blend the physical and digital ecosystems. While the clinical applications and technological challenges of DT are receiving growing attention, most existing studies remain focused on use-case scenarios, computational models, and engineering design (Haleem et al., 2023). Although these investigations offer valuable insights into DT's capabilities, they often overlook a critical aspect: the readiness and willingness of medical professionals to adopt DT systems in real-world clinical settings. This issue is especially important, as the successful adoption of emerging technologies depends as much on end-user acceptance as on technical innovation. The implementation of DT in healthcare necessitates a flexible systems management approach, where organizational preparedness, regulatory compliance, and managerial decision making change in step with the technology.

To address this gap in the literature, we pose the following question:

RQ1 What are the predicting factors influencing healthcare professionals' intention to adopt DT technology?

To address this question, we propose using an integrated model that combines UTAUT2 with the Technology-Organization-Environment (TOE) framework. Several theoretical models have been developed in the field of technology adoption research, including the technology acceptance model (TAM), the theory of planned behavior (TPB), and the diffusion of innovations (DOI). Each of these models offers a unique perspective (Barua & Barua, 2023); however, they often fall short in capturing the complex social, technical, and organizational contexts in which healthcare professionals operate. UTAUT2 improves upon earlier models by incorporating key individual-level constructs that reflect how clinicians perceive and intend to use new health technologies (Venkatesh et al., 2012a). Nevertheless, it does not sufficiently address broader technological, organizational, and environmental factors that influence adoption within institutional settings such as hospitals. The TOE framework complements this gap by integrating contextual dimensions, including organizational readiness, regulatory support, and technological compatibility, that are critical for understanding DT adoption in resource-constrained, policy-driven environments (Aligarh et al., 2023; Alkhater et al., 2018; Chittipaka et al., 2023).

Therefore, the integrated UTAUT2–TOE model provides a more comprehensive and robust theoretical foundation for examining DT adoption in healthcare settings, as well as its flexibility. It is equally important to understand the relative strength and practical significance of these predictors in influencing healthcare professionals' behavior toward adopting DT technologies. This type of analysis remains largely underexplored in existing literature. This leads us to our second research question:

RQ2 Among the UTAUT2 and TOE model constructs, which factors have a direct impact on healthcare professionals' behavioral intention to adopt DT, and how do these factors rank in importance?

It is apparent from RQ2 that this question builds upon the findings of RQ1. Through RQ2, we aim to examine the relative importance and predictive power of integrated UTAUT2–TOE constructs. While RQ1 helps us establish the conceptual framework, this study's core analytical aspect is obtained through RQ2. So, this study considers RQ2 as the key question, since it offers nuanced insights into the interaction among constructs. To address this RQ2, our study employs a state-of-the-art two-stage analytical approach that combines structural equation modeling (SEM) and artificial neural network (ANN) techniques. This hybrid method has gained widespread application in recent technology adoption studies and is increasingly favored by researchers (Alam et al., 2021; Arpaci et al., 2022; Mustafa et al., 2022a, 2022b; Suhail et al., 2024). We apply partial least squares SEM (PLS-SEM) to test the hypotheses derived from the UTAUT2 and TOE frameworks. Subsequently, ANN is used to predict and rank the importance of these factors based on their normalized significance. This comprehensive approach not only validates the proposed relationships between UTAUT2 and TOE constructs and the intention to adopt digital transformation, but also identifies the most influential predictors.

This prioritization is crucial for system designers, policymakers, and healthcare administrators seeking to allocate resources and design interventions that most effectively support the implementation of DT technologies in the healthcare sector, enabling flexible healthcare system management.

Theoretical Framework and Hypothesis Development

This research presents a conceptual framework for analyzing the adoption of DT technologies by healthcare practitioners. It examines how user perceptions and contextual factors influence adoption decisions in complex, regulated environments, such as healthcare, drawing on the UTAUT2 and TOE frameworks. UTAUT2 provides a robust foundation for understanding individual perceptions of technology, while TOE complements this by incorporating organizational and environmental readiness, together offering a comprehensive approach to analyzing DT adoption.

DT in Healthcare

The term "Digital Twin" (DT) was first introduced in the aerospace and manufacturing industries, where engineers used virtual replicas to model and test complex physical systems before investing in costly prototypes (Katsoulakis et al., 2024). A DT fundamentally consists of three elements: a physical entity, a virtual model, and a data connection that maintains synchronization between the two (Katsoulakis et al., 2024). Foundational technologies such as big data analytics, machine learning, cloud computing, and the Internet of Things (IoT) provide the continuous data streams and computational power required to support these virtual models (Machado & Berssaneti, 2023).

In healthcare, a DT can be defined as a virtual representation of a patient that enables dynamic modeling of treatment strategies, continuous monitoring, and health trajectory prediction based on clinical, genetic, environmental, and behavioral multi-modal data (Katsoulakis et al., 2024). Current applications of DT have already demonstrated significant success in patient-level modeling, hospital management, and clinical research. For example, cardiac twins help physicians plan therapies by simulating electrophysiological patterns. Artificial pancreas devices illustrate how DTs can integrate real-time monitoring with intervention by delivering insulin and maintaining normoglycemia using glucose sensor data and predictive algorithms (Meijer et al., 2023). Hospitals also employ virtual models of radiology departments or operating rooms to evaluate resource allocation strategies, optimize productivity, and reduce patient wait times (Meijer et al., 2023). Moreover, researchers are exploring the use of DTs as platforms for in-silico trials, enabling the testing of surgical techniques or drug responses on virtual cohorts before conducting costly clinical studies (Katsoulakis et al., 2024). Even though DT is capable of introducing these advantages into the healthcare, its adoption in healthcare may face several challenges due to the barriers posed by data integration and interoperability (Sasitharasarma et al., 2025). Especially, for a large-scale DT deployment, large investment, security risk, and ethical concerns can make things for complicated. Moreover, limited digital infrastructure and lack of skilled personnel will slow down successful implementation of DT in developing countries like Bangladesh. Addressing these challenges and limitations is crucial for fully utilize DT in attaining flexible healthcare management. While research into the technological aspects of DT is expanding, studies focused on user acceptance of DT in healthcare remain scarce. In response, this study seeks to investigate the acceptability of DT among healthcare users, thereby contributing to the limited body of literature in this area.

Flexible Management in Healthcare and DT

Flexibility in healthcare refers to the ability to modify procedures, distribute resources efficiently, and provide individualized treatment in response to environmental and patient demands (Bera et al., 2023). Given that the healthcare industry frequently faces emergencies and disruptions, many scholars consider flexible management practices essential for hospitals and clinics (Giri et al., 2024). Ojeda et al. (2025) demonstrated that digital technologies, such as AI and big data, can facilitate adaptive and flexible strategies in complex environments (Ojeda et al., 2025). Thus, in resource-constrained complex environments like healthcare, flexible practices are necessary, and digital technologies can act as cornerstones for embedding flexibility into healthcare systems.

DT technologies stand out among digital innovations as powerful enablers of healthcare flexibility. DTs can help the healthcare management to assess the evolving system needs, which promotes institutional flexibility by regulatory alignment and policy adaptation (Daraio et al., 2025). By allowing for patient-level adaptive treatment, Meijer et al. (2023) demonstrate how DT-based artificial pancreas systems combine monitoring and intervention, showcasing operational flexibility (Meijer et al., 2023). Likewise, Katsoulakis et al. (2024) stress how DT compatibility with current infrastructure guarantees integration with various health information systems and improves technological flexibility (Katsoulakis et al., 2024). As a result, DT offers a multifaceted basis for flexible management practices in healthcare, enabling organizations to adhere to evolving regulations, providing healthcare practitioners with the tools to dynamically modify workflows, and supporting technical ecosystems that adapt to new clinical demands. Although several studies have shown that DT can be technically applied successfully in a variety of ways in healthcare, many of these initial experiences were either based on small-scale pilot projects or conducted in highly-specialized clinical environments (e.g., cardiology, oncology, and surgical simulation) (Chauhan & Bahad, 2025; Katsoulakis et al., 2024; Meijer et al., 2023). However, institutional and professional acceptance of DT remains in its earliest stages of development. This is particularly true for LMICs where DT integration may face varying levels of development of infrastructure, governance, and readiness of behavior (Umah et al., 2025). So, the current issue is no longer whether DT can be applied in healthcare, but rather, whether healthcare professionals are ready and willing to adopt and incorporate DT as an integral part of their daily work. Therefore, assessing the willingness to adopt DT is critical to help close the gap between the potential of DT and its practical application. This will allow for the identification of organizational, regulatory, and human enablers needed for scalable DT integration.

Integrating UTAUT2 and TOE for Digital Twin Adoption

Various studies have explored user acceptance of new technologies using the UTAUT and UTAUT2 models (Arpaci et al., 2022; Barua & Barua, 2023; Suhail et al., 2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) was first introduced by Venkatesh et al. (2003) to evaluate and synthesize several existing models. They formulated a unified theory of technology adoption and empirically validated it. Later, Venkatesh et al., (2012a) developed UTAUT2, an extended version of the original model designed to adopt a more user-centered perspective that accounts for how individuals interact with technology. According to UTAUT2, seven core constructs influence behavioral intention (BI) to use technology: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HB). These relationships are further moderated by age, gender, and experience (Venkatesh et al., 2012a). UTAUT2 has proven useful in studying the adoption of mobile health (mHealth), electronic health (eHealth), and other healthcare technologies. For example, Huang and Yang (2020) used UTAUT2 to examine the use of an AI-powered mobile app for weight loss and health maintenance, while Barua and Barua (2023) investigated mobile health adoption among refugees. UTAUT2 constructs like EE and FC focus not only on adoption intention but also provide guidelines for flexible managerial action.

Given that DT adoption in healthcare often involves mobile-enabled dashboards, cloud-based visualizations, wearable-integrated patient data, and real-time simulations (Haleem et al., 2023), UTAUT2 is well-suited for this research context. Accordingly, UTAUT2 was selected as one of the frameworks for our study. Empirical research in healthcare consistently shows that PE and EE positively influence BI (Yousef et al., 2021), while the effects of SI, FC, and HM vary depending on contextual factors (Mensah et al., 2022).

However, not all constructs within UTAUT2 are equally relevant in every setting. In this study, hedonic motivation and habit were excluded due to contextual considerations. Hedonic motivation, which reflects the pleasure or enjoyment derived from using a system, is more applicable to consumer technologies. In contrast, healthcare professionals adopt technologies primarily for therapeutic utility, operational efficiency, and regulatory compliance rather than enjoyment. Similarly, habit defined as automatic behavior developed through repeated use is less applicable in Bangladesh, where DT is still in its early adoption phase and lacks widespread familiarity (Hossain et al., 2025). Following Mustafa et al., (2022a, 2022b), we incorporated perceived functional value (PFV) into the UTAUT2 model to better capture healthcare professionals' utilitarian perspectives when evaluating DT technologies.

While UTAUT2 is a robust model for understanding individual-level technology adoption, it falls short in fully explaining the adoption of Digital Twin (DT) systems in healthcare. DT technologies are complex, organization-level innovations that require not only individual user acceptance but also institutional readiness, technological integration, and adherence to regulatory standards (Botín-Sanabria et al., 2022). To address these broader organizational factors, various studies have integrated the Technology-Organization-Environment (TOE) framework with UTAUT2. For example, Ates and Polat (2025) employed a combined UTAUT2-TOE approach to examine the adoption of humanoid robots by science instructors in Turkey. In their model, UTAUT2 captured individual-level factors, while the TOE framework accounted for organizational and environmental influences, resulting in a comprehensive understanding of both personal and contextual determinants. Similarly, Haripin and Warsono (2024) used the integrated UTAUT2-TOE model to study the adoption of SIDEK-Edu, an e-learning platform, by Indonesian high school students. Although no existing study has applied the UTAUT2-TOE framework to investigate technology adoption in the healthcare sector specifically, the integrated model is well-suited for this context.

Tornatzky and Fleischer (1990) developed the Technology-Organization-Environment (TOE) framework to explain how organizational units adopt and implement new technologies. According to this framework, three key contexts technological, organizational, and environmental collectively influence the adoption of information systems (Gupta & Shankar, 2022; Ojeda et al., 2025). Unlike other theoretical models, TOE uniquely considers all dimensions that may impact IT adoption initiatives as it analyzes technology usage, adoption, and value development (Owusu, 2020). The technological context in the TOE framework highlights how the characteristics of available technologies affect adoption decisions. The most commonly discussed constructs in the literature under this category include relative advantage (RA), compatibility (COM), and complexity (CLX) (Alkhater et al., 2018; Chittipaka et al., 2023; Qutaishat et al., 2023). The organizational context refers to the internal characteristics and resources of a firm, encompassing both tangible and intangible assets (Chittipaka et al., 2023; Gide & Sandu, 2015). Several studies have identified specific factors within this domain, with higher authority support (HAS) and organizational readiness (ORR) being among the most frequently cited (Alsetoohy et al., 2019; Soomro et al., 2025). Consequently, these two organizational factors are included in this study.

Environmental variables encompass industry characteristics, market structure, and the regulatory framework, collectively forming the external environment in which an organization operates. Tornatzky and Fleischer (1990) identified three key environmental elements: industry characteristics, government regulations, and technological infrastructure. Among these, regulatory support (RS) has been identified in previous research as the primary environmental factor influencing technology adoption within the TOE framework (Alraja et al., 2022; Chittipaka et al., 2023). In this study, RS is included as a predictor variable, as it is often essential for the adoption of new technologies in healthcare due to concerns around data privacy, liability, and clinical safety. TOE constructs like RA, COM, RS, etc. are important for measuring the management's ability to be flexible, since existing workflows, clinical pathways, and policies have to be adjusted when DT is introduced. Since DT in healthcare will deal with sensitive data, regulation and governance will play a crucial role in DT adoption for flexible management. RS and HAS reflect the presence of governance at the policy as well as at the institutional level. Government and managerial oversight, data privacy, ethical frameworks, and leadership accountability can be in practice through RS and HAS (Halim et al., 2023; Hesarzadeh, 2020). Furthermore, ORR not only encompasses the technological readiness but also whether the management is flexible enough to integrate and maintain audit readiness and government policies (Aini & Djoko Setyadi, 2022; Putri et al., 2025). By integrating the TOE framework with the UTAUT2 model, this study addresses both the individual-level factors influencing DT user acceptance and the broader organizational and environmental and governance considerations. This integrated theoretical approach provides a more comprehensive representation of the complex landscape of DT adoption in healthcare flexible systems. The proposed research model is illustrated in Fig. 1.

Hypothesis Development

UTAUT2 Constructs and Behavioral Intention (BI)

Performance expectancy (PE) is the confidence that a technological tool will enhance one's efficiency and effectiveness at work (Mustafa et al., 2022a, 2022b). Venkatesh et al., (2012a) stated that PE is a significant predictor of BI. With the help of DT systems, healthcare providers can benefit from more rapid diagnoses, more accurate treatment planning, and more efficient use of resources through predictive simulations and patient-specific modeling (Haleem et al., 2023). It is more probable that healthcare practitioners will implement DT if they believe that it will improve their clinical efficacy. We can formulate our first hypothesis as:

Hypothesis 1. Performance expectancy (PE) positively influences healthcare professionals' BI to adopt DT.

Effort expectancy (EE) is a measure of how easy a system is thought to be to learn and use (Venkatesh et al., 2012a). Complex or time-consuming technology tends to be avoided by healthcare practitioners in high-pressure, time-sensitive situations such as hospitals. EE has been proven to be a very important predictor of the intention to use newer technologies by various studies (Barua & Barua, 2023; Venkatesh et al., 2003, 2012a). Thus, we can theorize that:

Hypothesis 2. Effort expectancy (EE) positively influences healthcare professionals' BI to adopt DT.

Social influence (SI) can be defined as the extent to which an individual considers the opinions of others to be influential enough to justify using a new technology (Venkatesh et al., 2012a). Clinicians are more inclined to employ DT if they observe that their colleagues or supervisors are doing it, or if those in charge of academic institutions advocate for it. Although the professionals are more inclined to use DT in the organization primarily

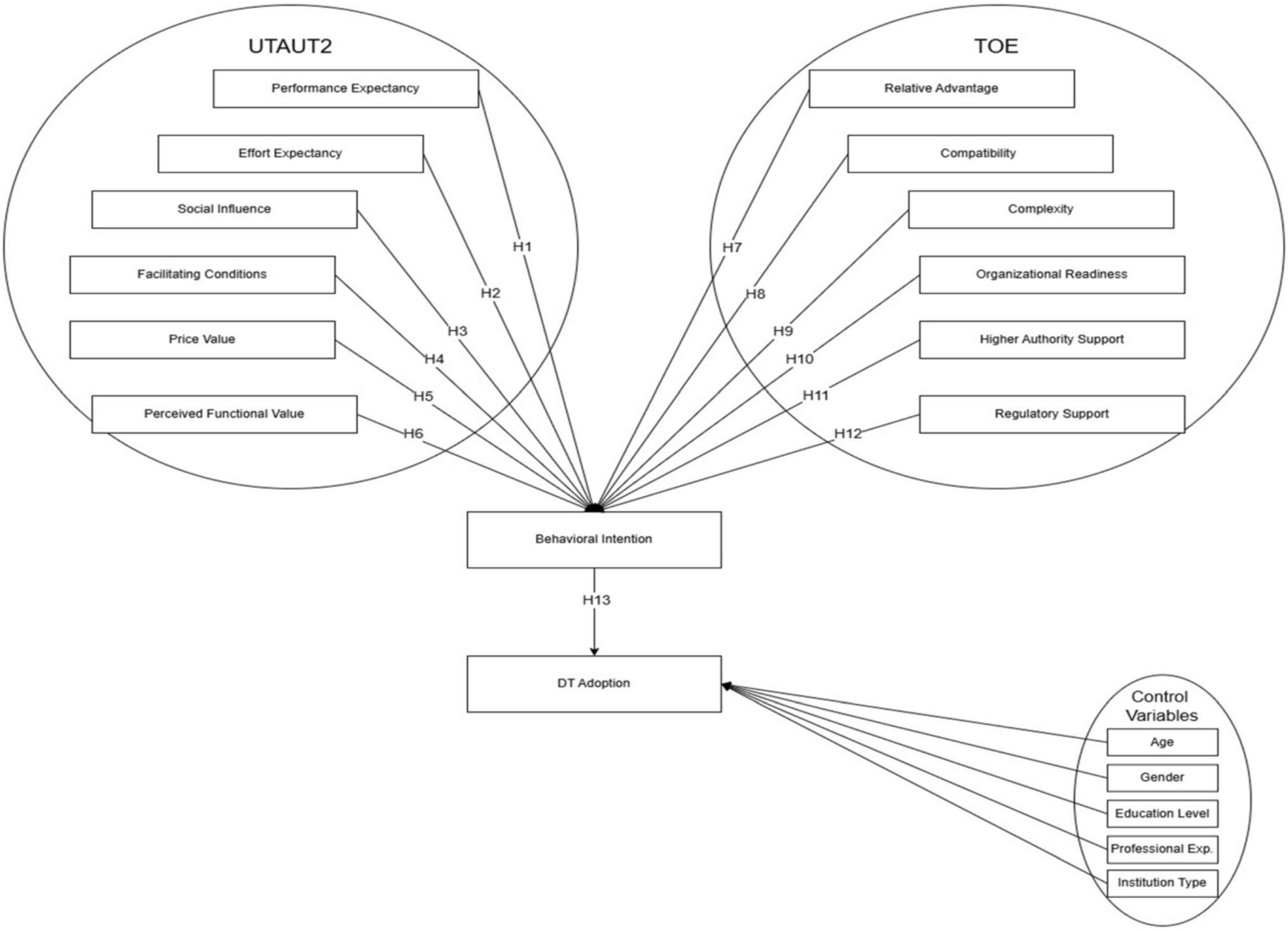


Fig. 1 Research model

based on functionality, it is possible to be influenced by other professionals' opinion and their acceptance of DT technologies (Mustafa et al., 2022a, 2022b). Thus, we argue that:

Hypothesis 3. Social influence (SI) positively influences healthcare professionals' BI to adopt DT.

Facilitating condition (FC) is the level of confidence a person has that there is an organizational and technical infrastructure in place to enable the use of the system (Venkatesh et al., 2003). Both the intention to use technology and customers' health-conscious attitude toward technology adoption are positively correlated with FC (Rahaman et al., 2023). There is strong evidence from prior research that FC is a key predictor for healthcare technology adoption (Alam et al., 2021). In clinical settings, where technology typically needs to work with current health information systems, strong support, and infrastructure are pretty important. So, we can theorize that:

Hypothesis 4. Facilitating conditions (FC) positively influence healthcare professionals' BI to adopt DT.

Price value (PV) is described as the cognitive trade-off users evaluate when considering the benefits of a system relative to its perceived costs, which may be financial, behavioral, or temporal (Bommer et al., 2024; Venkatesh et al., 2012a). Although healthcare personnel typically do not bear the costs of technology, the governing body must acknowledge the substantial expenditure necessary for the comprehensive integration of digital transformation technologies into the hospital system. Perceived value is positively correlated with technology adoption among health-conscious consumers (Mustafa et al., 2022a, 2022b) and served as a strong predictor of behavioral intention for mHealth during the COVID-19 pandemic (Alam et al., 2021). These facts compel us to assert that:

Hypothesis 5. Price value (PV) positively influences healthcare professionals' BI to adopt DT.

The perceived functional value (PCV) of a product or technology is its perceived usefulness, performance, and quality in the eyes of the buyer (Venkatesh et al., 2012a). Numerous studies indicate that if a product delivers exceptional functional value, end users embrace it rapidly (Bhardwaj & Sharma, 2021; Mustafa et al., 2022a, 2022b; Nath & Wu, 2020). Digital technologies that assist doctors in enhancing decision making, monitoring patients in real time, or refining procedural planning will be seen as functionally helpful (Sun et al., 2023). Based on these observations, we can postulate that:

Hypothesis 6. Perceived functional value (PFV) positively influences healthcare professionals' BI to adopt DT.

TOE Constructs and Behavioral Intention

Relative advantage (RA) denotes the extent to which a technology is regarded as superior to current methods or technologies (Chittipaka et al., 2023). Digital technologies markedly improve conventional decision support tools through the facilitation of real time, patient-specific modeling, simulation, and predictive analytics (Haleem et al., 2023; Sun et al., 2023). The integration of data from wearable sensors, medical devices, imaging systems, and electronic health records (EHRs) enables digital twins to form a dynamic virtual representation of a patient or process (Sun et al., 2023), in contrast to traditional systems that depend on static protocols or retrospective data. Research demonstrates that RA notably influences the rate of technology adoption within organizations (Aligarh et al., 2023; Alkhater et al., 2018; Chittipaka et al., 2023). It is proposed that:

Hypothesis 7. Relative advantage (RA) positively influences healthcare professionals' BI to adopt DT.

Compatibility (COM) is the degree to which new technology fits with an organization's current needs, traits, and ways of doing things (Rogers, 1995). Professionals are more likely to use digital transformation technologies when they can be easily added to existing electronic health records, clinical procedures, and departmental rules. COM serves as a crucial predictor of the adoption of new technologies within organizations (Amini & Jahanbakhsh Javid, 2023). It is proposed that:

Hypothesis 8. Compatibility (COM) positively influences healthcare professionals' BI to adopt DT.

Complexity (CLX) is defined as the level of innovation that people think it has, which is rather hard to understand and apply (Aligarh et al., 2023). There is a negative relationship between complexity and the adoption of new technology. The more complex something is, the faster it is adopted. On the other hand, the more complicated the invention is, the harder it will be to use (Aligarh et al., 2023; Bauer et al., 2005). In the high-stakes healthcare field, where mistakes can have serious consequences, experts may not want to use technology that seems too complicated, strange, or does not have an intuitive design. Based on these findings, we can argue that:

Hypothesis 9. Complexity (CLX) negatively influences healthcare professionals' BI to adopt DT.

Organizational readiness (ORR) is a measure of the extent to which a company has implemented critical measures, such as IT infrastructure, financial resources, and employee proficiency to accomplish its objectives (Putri et al., 2025). ORR also indicates whether the organization has policy preparedness that ensures that management adheres to standard data management, audit protocols (Aini & Djoko Setyadi, 2022). In managing the costs and technical demands associated with the adoption of modern technologies, such as cloud accounting or digital transformation systems, organizations that have sufficient financial resources and appropriate IT infrastructure have a competitive advantage. The preparedness and readiness of organizations have an impact on both technology adoption and performance (Putri et al., 2025). We hereby present our recommendation:

Hypothesis 10. Organizational readiness (ORR) positively influences healthcare professionals' BI to adopt DT.

The concept of higher authority support (HAS) pertains to the extent to which managers comprehend and feel at ease with the technologies that have recently been introduced (Maroufkhani et al., 2020). The endorsement of the initiative by upper management can significantly ease the transition to new technology by fostering a supportive organizational atmosphere (Dutta et al., 2020). Endorsement from senior leadership is crucial for fostering acceptance in structured settings such as healthcare, where directives from above frequently drive systemic transformation. The adoption of newer technologies can be favorably impacted by HAS, as evidenced by numerous studies (Aligarh et al., 2023; Chittipaka et al., 2023; Oliveira et al., 2019). We put forth the subsequent hypothesis:

Hypothesis 11. Higher authority support (HAS) positively influences healthcare professionals' BI to adopt DT.

Regulatory support (RS) refers to the laws, regulations, and compliance duties imposed by the government and other authorities on enterprises (Amini & Jahanbakhsh Javid, 2023). This is done to monitor and regulate industries that implement new technologies. Government rules that are already in motion can encourage or discourage organizations to adopt DT (Rath et al., 2012) since in healthcare data privacy, medical ethics, and liability concerns are high, professionals are more likely to adopt DT systems that are legally sanctioned, secure, and in line with institutional or national policy. So, we can argue that:

Hypothesis 12. Regulatory support (RS) positively influences healthcare professionals' BI to adopt DT.

Behavioral Intention and DT Adoption (DA)

It is well-established that behavioral intention is a predictor of actual technology use (Mustafa et al., 2022a, 2022b). Adoption is based on the central idea that "actual usage" projects an individual's "intention" to implement new technologies (Venkatesh et al., 2012a). Venkatesh et al., (2012a) explained that BI and actual use have the same importance when it comes to new technology adoption. BI and actual adoption have been used in numerous technology adoption studies as explanatory variables (Alam et al., 2021; Mustafa et al., 2022a, 2022b; Venkatesh et al., 2003, 2012a). It has also been shown in the literature that people are more likely to adopt new technology if they have faith in their ability to use it (Ajzen, 1991). Intentions are nearly inseparable from technology usage. An individual's reaction to using technology is intricately related to its adoption. If external factors permit, healthcare providers' strong intentions to employ DT usually result in acceptance and DT adoption (DA). Thus, the findings of these studies lead us to hypothesize that:

Hypothesis 13. Behavioral intention (BI) positively influences actual adoption and use of DT in healthcare.

Control Variables

Whether people are more likely to embrace a new product or technology depends heavily on demographics (Mustafa et al., 2022a, 2022b). Researching demographics is vital for ensuring DA. As people grow old, they increasingly become resistant to trying out newer technologies, as they are comfortable with their old technologies (Laukkanen, 2016). In research on technology adoption, gender and age have been examined in many ways, including as moderators and control variables (Mustafa et al., 2022a, 2022b; Venkatesh et al., 2012a). Another control variable to examine when evaluating technology adoption is education level (Dahabiyeh et al., 2021). In the case of healthcare studies, it is also important to account for the institution type such as public and private (Yang et al., 2020). Furthermore, professional experience has been a key control variable in various technology adoption studies (V. Gupta, 2024). This variable has adapted in three categories in our study, such as less than 5 years, 5–15 years, and more than 15 years. Thus, to account for possible demographic influences on the BI's adoption of DT, this study incorporates age, gender, education level, institution type, and experience level as control variables. Although gender, age, and institution type may influence views toward digital tools, education level and experience level are anticipated to have a more direct impact in our study because more knowledge and experience may boost one's confidence in utilizing complex, data-driven technology like DT. Thus, we expect these control variables to have a significant impact on DA in healthcare organizations.

Methodology

This study employed an empirical survey to investigate the factors influencing DT acceptance among healthcare professionals. The research model was evaluated using SmartPLS 4.0 to assess both the measurement and structural models. Subsequently, the importance of the constructs was determined through ANN analysis, conducted using SPSS 25.

Survey Instrument and Data Collection

Most of the constructs in the UTAUT2 and TOE were obtained from previously validated research, which served as the basis for the instrument used in this study. We measured PFV, PE, EE, SI, FC, and PV via the scale given by the UTAUT2 model (Venkatesh et al., 2012a). The scale for ORR, RS, RA, COM, HAS, and CLX was adapted from different studies focused on the TOE framework (Aligarh et al., 2023; Alkhater et al., 2018; Chittipaka et al., 2023; Ghobakhloo et al., 2011; Wu & Chen, 2014). The instrument was reviewed by five academics and a panel of ten members, whose feedback on the constructs and scales was incorporated (Gunawan et al., 2021). This was done to ensure content validity, contextual relevance, and linguistic clarity since this study is mainly centered around Bangladeshi healthcare environment and the adapted measurement items were drawn from studies that might have different contextual and cultural theme. To ensure that the amount of time and comments given by respondents will not have a detrimental effect on the quality of the survey, a pilot study was carried out (Kost & da Rosa, 2018). Students at different study levels (Master's and Bachelor's) and five healthcare professionals were involved in the pilot study (Chipeva et al., 2018). The participation of postgraduate and undergraduate students in the pilot study was limited to evaluation of the clarity, sequence and understandability of the survey, and not the examination of theoretical constructs. We also engaged with academic experts and incorporated their suggestions during the pilot study. We consulted a language specialist to convert our instrument from English into Bengali for the target demographic.

The healthcare organizations are the unit of analysis in this study, and the survey questionnaire was designed to be filled out by a single respondent. The healthcare organizations (i.e., hospitals, clinics, healthcare associations, and councils) were contacted through email, which were obtained from their websites. After a series of internet searches, 600 healthcare organizations were found to be using modern technologies. The target participants were mainly physicians, nurses, and healthcare administrators who already had a good understanding of simulations and DT technologies. These 600 organizations were contacted by email in January 2025. However, volunteer engagement may lead to self-selection bias in a random sample strategy that reaches out to many groups. The sample may be unrepresentative if respondents differ systematically from non-responders. A mix of stratified sampling, targeted recruiting of participants with relevant digital experience, and numerous reminder emails was used to address this issue. These tactics improved representativeness and reduced bias in survey-based studies, especially those on specialist issues (Hernán et al., 2004).

At the end of March 2025, after three waves of reminders, we managed to collect 439 valid responses. A random sampling method was employed for data collection. The results show that 73.16% of people were surveyed. Based on earlier validation by several studies that mainly employed survey-based analysis, the achieved response rate is sufficient for the investigation of this study framework (Gupta et al., 2019; Hossain et al., 2025). Using a five-point Likert scale, where 5 indicates strong agreement and 1 implies strong disagreement, the participants were given the chance to express their opinions about the items given to them. In Table 1, the demographics of 439 respondents, such as gender, education level, age, organizational role, experience with digital technologies, and experience in healthcare, are presented. Appendix A includes all the measurement item constructs and their sources and the revised versions of the measurement items are illustrated in Appendix B.

Common Method Bias

A single-response survey has the potential to be subjected to common method bias (CMB) (Podsakoff et al., 2003). Qualitative interviews were used to determine the difficulty of understanding the questions. According to the feedback that we received, some questions were altered. Another cause of CMB is item ambiguity (Podsakoff et al., 2003), which may make it harder to identify relevant information or make good decisions (Krosnick, 1991) Thus, the questions were simplified to lessen respondents' discomfort. Two-fold questions are also a major source of CMB (Krosnick, 1991). We altogether avoided these questions. Retrospective questions might stress responders, making it harder to get accurate answers (Krosnick, 1991). To mitigate their stress, the questions were designed to analyze the current situation, allowing respondents to respond instantly. Standard single-factor Harman's test and procedural remedies were used. We found from the results of this test that a single component explained 24% of the variance, below the suggested 50% (Kock, 2020). This test shows no CMB issues in the data. Some scholars believe that the single-factor Harman's test is ineffective for assessing common method variance (CMV), although it is helpful in analyzing data from a single participant (Podsakoff et al., 2003). So, in addition, the correlation marker method was used to study CMB (Lindell & Whitney, 2001). We used the formulae employed by Lindell and Whitne (2001) to evaluate correlation significance. Upon comparing the adjusted and unadjusted correlations, we observed minimal differences. Based on these results, we determined that CMV is not a significant factor for our study.

Data Analysis and Results

Integrated SEM-ANN Approach

The connections between different latent variables can be statistically confirmed through various methodologies, such as SEM, factor analysis, and regression analysis (Mai & Liao, 2022). The majority of academics opted for SEM analysis because of its greater sophistication and advancement relative to other methods (Hair Jr et al., 2010; Hossain et al., 2025).

The partial least squares (PLS) method was selected for this investigation. This approach is grounded in variance and aligns with the structural equation modeling framework. PLS finds extensive application in contemporary information systems, investigations into emerging technologies, and the fields of social and economic sciences (Barua & Barua, 2023). PLS does not necessitate the dataset to adhere to multivariate normality, in contrast to the covariance-based SEM approach (Jain et al., 2012). One benefit of employing path modeling with PLS is the capacity to assess outcomes on a global level, which includes the overall model, as well as on a local level, concentrating on the measurement and structural models (Henseler et al., 2016). In contrast to the covariance-based SEM approach, the dataset in PLS does not require multivariate normality (Jain et al., 2012).

An artificial neural network (ANN) simulates the neural network structures of the human brain and acquires information through learning processes (Hew et al., 2018). Furthermore, Hew et al. (2018) shown that artificial neural networks (ANNs) can improve their efficiency owing to their learning capabilities. In comparison with other multivariate models like SEM, ANN is distinguished by its

Table 1 Demographic information

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	195	44.42
	Female	244	55.58
Education level	College or less	44	10.00
	Bachelor/MBBS	145	33.00
	Masters/MPH	175	39.90
	Doctorate/MD	75	17.10
Age	Less than 25	31	7.10
	26–40	294	67.00
	More than 40	114	26.00
Organizational role	Physician	118	26.90
	Nurse	145	33.00
	Healthcare Administrator	75	17.10
	Doctor	101	23.00
Experience with digital tech	Basic (uses hospital EMRs, telemedicine)	119	27.10
	Moderate (uses health analytics)	206	46.90%
	Advanced (uses simulations)	114	26.00
Experience in healthcare	Less than 5 years	88	20.00
	5–15 years	233	53.10
	More than 15 years	118	26.90
Institution type	Public	210	47.83
	Private	229	52.17

learning capacity, which significantly improves its predictive performance and guarantees consistent results (Mustafa et al., 2022a, 2022b). Also, typical multivariate studies like SEM are hampered by ANN's "black-box" approach, which makes it impossible to judge the importance of causal interactions, so it can't be used to test hypotheses (Mustafa & Zhang, 2023). That's why numerous researchers have suggested that combining SEM and ANN investigations is beneficial, using the strengths of both different analytical methodologies and they also suggested that integrating SEM and ANN can equilibrate and yield a more thorough data examination (Barua & Barua, 2023; Mustafa & Zhang, 2023; Mustafa et al., 2022a, 2022b). Following typical procedures in other studies for conducting a dual analysis, SEM was initially employed to identify the significant exogenous constructs. After that, these constructs were used as input neurons in the ANN analysis. This was done to gain a thorough understanding of the nonlinearity that exists among the predictor constructs (Arpaci et al., 2022).

Measurement model assessment

We used reflective constructs in our study. First, scale composite reliability (SCR) and average variance extracted (AVE) for each construct and factor loadings for each measuring item were calculated so that measurement model validity and reliability could be assessed (Fornell & Larcker, 1981). Table 2 presents the results of the confirmatory factor analysis (CFA). Measurement items are considered suitable for PLS-SEM analysis if their factor loading values are 0.5 or higher (Hair et al., 2017). All factor loading values for each measurement item were greater than 0.5. According to Table 2, the SCR and AVE values are higher than the set limits of 0.7 and 0.5, respectively (Henseler et al., 2016). At both the indicator and construct levels, convergent validity is good enough (Fornell & Larcker, 1981). We used Cronbach's alpha to check how accurate and consistent the model was for each construct. The alpha values of the measurement model in Table 2 are higher than 0.6, which means it is reliable and consistent (Molina et al., 2007).

Second, a discriminant validity test was conducted to examine the problems with discriminant validity in the structural model. To assess divergent validity, we employed the criteria established by Fornell and Larcker (1981) in conjunction with the HTMT (heterotrait—monotrait ratio of correlations) technique (Henseler et al., 2016). We built the inner-correlation matrix using the method that Fornell and Larcker (1981) set up. The square

Table 2 Construct reliability and validity

Construct	Item	VIF	Loading	Cronbach's alpha	CR	AVE
Behavioral intention	BI1	4.877	0.949	0.946	0.965	0.903
	BI2	5.918	0.962			
	BI3	4.102	0.940			
Compatibility	COM1	5.754	0.953	0.923	0.952	0.867
	COM2	2.472	0.892			
	COM3	5.438	0.948			
Complexity	CLX1	5.005	0.888	0.859	0.903	0.699
	CLX2	3.609	0.753			
	CLX3	3.939	0.814			
	CLX4	4.596	0.883			
DT adoption	DA1	3.241	0.875	0.907	0.931	0.731
	DA2	4.486	0.918			
	DA3	2.821	0.878			
	DA4	2.467	0.851			
	DA5	1.665	0.741			
Effort expectancy	EE1	4.594	0.909	0.940	0.957	0.848
	EE2	4.758	0.918			
	EE3	4.969	0.927			
	EE4	5.331	0.929			
Facilitating conditions	FC1	5.418	0.898	0.933	0.952	0.832
	FC2	5.155	0.917			
	FC3	5.181	0.921			
	FC4	5.906	0.912			
Organizational readiness	OR1	7.894	0.917	0.942	0.956	0.813
	OR2	9.222	0.924			
	OR3	3.492	0.842			
	OR4	11.224	0.918			
	OR5	8.835	0.906			
Perceived functional value	PFV1	2.33	0.933	0.861	0.935	0.878
	PFV2	2.33	0.940			
Performance expectancy	PE1	3.936	0.936	0.927	0.954	0.873
	PE2	3.061	0.913			
	PE3	4.887	0.954			
Price value	PV1	1.951	0.846	0.843	0.905	0.761
	PV2	2.382	0.902			
	PV3	1.904	0.868			
Regulatory support	RS1	5.53	0.958	0.950	0.968	0.910
	RS2	5.718	0.960			
	RS3	4.346	0.944			
Relative advantage	RA1	6.448	0.945	0.953	0.966	0.877
	RA2	8.673	0.962			
	RA3	3.623	0.918			
	RA4	4.214	0.920			
Social influence	SI1	1.516	0.813	0.763	0.864	0.679
	SI2	1.496	0.818			
	SI3	1.707	0.840			

Table 2 continued

Construct	Item	VIF	Loading	Cronbach's alpha	CR	AVE
Higher authority support	HAS1	5.535	0.917	0.945	0.960	0.857
	HAS2	6.562	0.927			
	HAS3	5.905	0.927			
	HAS4	6.508	0.933			

root of the AVE values makes up the main diagonal elements in Table 3. The square root values of the average variance extracted (AVE) for all latent variables are higher than the correlation coefficients for those variables in the same column. This shows that the variables are discriminant valid (Fornell & Larcker, 1981). We used the HTMT criterion to compare the average correlations of observations that were in the same latent variable to those that were in separate latent variables. This showed that the model worked. The values of all reflective constructs are less than 0.85, indicating that they exhibit discriminant validity as shown in Table 4 (Henseler et al., 2016).

Path Analysis

A resample size of 5000 was used in the bootstrapping method of SmartPLS 4.0 (Hair et al., 2017) to evaluate whether the hypotheses are significant where p-value $<$ 0.05 (Efron & Tibshirani, 1994). In Table 5, the path coefficient (β) and t-value are shown along with the p-values obtained from the PLS-SEM analysis.

Our findings show that all six UTAUT2-based hypotheses were supported with statistically significant results. Effort expectancy ($\beta = 0.187$, $p < 0.001$) and facilitating conditions ($\beta = 0.188$, $p < 0.001$) were the strongest predictors among UTAUT2 constructs, indicating that perceived ease of use and the availability of technical and organizational support are really important of DT adoption. Performance expectancy ($\beta = 0.103$, $p = 0.006$) and price value ($\beta = 0.082$, $p = 0.005$) also had significant positive effects on behavioral intention. Perceived functional value ($\beta = 0.055$, $p = 0.023$) and social influence ($\beta = 0.054$, $p = 0.034$) were the least influential among UTAUT2 constructs but still statistically significant, suggesting that practical utility and peer opinions have a moderate impact on intention to use.

All TOE-related hypotheses were also supported. Among the TOE constructs, regulatory support ($\beta = 0.188$, $p < 0.001$) and compatibility ($\beta = 0.165$, $p < 0.001$) were the biggest predictors of behavioral intention, emphasizing the importance of external policy alignment and integration with existing workflows. Organizational readiness

Table 3 Fornell-Larcker criterion for discriminant validity

	BI	COM	CLX	DA	EE	FC	OR	PFV	PE	PV	RS	RA	SI	HAS
Behavioral intention (BI)	0.950													
Compatibility (COM)	0.729	0.931												
Complexity (CLX)	0.410	0.300	0.836											
DT adoption (DA)	0.278	0.242	0.110	0.855										
Effort expectancy (EE)	0.797	0.616	0.350	0.294	0.921									
Facilatating conditions (FC)	0.790	0.560	0.390	0.272	0.613	0.912								
Organizational readiness (OR)	0.675	0.495	0.359	0.168	0.524	0.589	0.902							
Perceived functional value (PFV)	0.668	0.576	0.319	0.300	0.642	0.521	0.469	0.937						
Performance expectancy (PE)	0.791	0.561	0.390	0.262	0.686	0.757	0.559	0.538	0.934					
Price value (PV)	0.696	0.517	0.445	0.215	0.579	0.599	0.551	0.506	0.625	0.872				
Regulatory support (RS)	0.696	0.505	0.479	0.168	0.549	0.560	0.454	0.446	0.568	0.455	0.954			
Relative advantage (RA)	0.698	0.540	0.314	0.317	0.660	0.573	0.524	0.545	0.583	0.542	0.483	0.937		
Social influence (SI)	0.686	0.475	0.371	0.287	0.620	0.579	0.516	0.552	0.672	0.611	0.455	0.529	0.824	
Higher authority support (HAS)	0.598	0.423	0.440	0.203	0.496	0.526	0.470	0.455	0.531	0.592	0.422	0.408	0.528	0.926

Table 4 Heterotrait-Monotrait ratio (HTMT) for discriminant validity

	BI	COM	CLX	DA	EE	FC	OR	PFV	PE	PV	RS	RA	SI	HAS
Behavioral intention (BI)	–													
Compatibility (COM)	0.780	–												
Complexity (CLX)	0.442	0.324	–											
DT adoption (DA)	0.299	0.263	0.125	–										
Effort expectancy (EE)	0.845	0.660	0.379	0.318	–									
Facilatating conditions (FC)	0.837	0.601	0.418	0.294	0.650	–								
Organizational readiness (OR)	0.708	0.527	0.383	0.183	0.552	0.618	–							
Perceived functional value (PFV)	0.740	0.646	0.360	0.340	0.713	0.578	0.516	–						
Performance expectancy (PE)	0.844	0.605	0.421	0.283	0.733	0.811	0.594	0.601	–					
Price Value (PV)	0.776	0.584	0.505	0.242	0.648	0.672	0.616	0.590	0.706	–				
Regulatory support (RS)	0.734	0.540	0.511	0.179	0.580	0.590	0.474	0.494	0.606	0.505	–			
Relative advantage (RA)	0.734	0.575	0.338	0.340	0.697	0.605	0.551	0.601	0.619	0.604	0.508	–		
Social influence (SI)	0.805	0.565	0.448	0.341	0.731	0.681	0.605	0.680	0.798	0.757	0.532	0.619	–	
Higher authority support (HAS)	0.632	0.453	0.473	0.219	0.526	0.556	0.498	0.505	0.567	0.665	0.446	0.429	0.621	–

Table 5 Hypothesis testing results

Hypothesis	Path Coefficient (β^2)	*T* statistics	*P*-value	Result
H1: Performance Expectancy (PE) positively influences healthcare professionals' BI to adopt DT	0.103	2.512	0.006	Accepted
H2: Effort Expectancy (EE) positively influences healthcare professionals' BI to adopt DT	0.187	5.097	0.000	Accepted
H3: Social Influence (SI) positively influences healthcare professionals' BI to adopt DT	0.054	1.826	0.034	Accepted
H4: Facilitating Conditions (FC) positively influence healthcare professionals' BI to adopt DT	0.188	4.843	0.000	Accepted
H5: Price Value (PV) positively influences healthcare professionals' BI to adopt DT	0.082	2.597	0.005	Accepted
H6: Perceived Functional Value (PFV) positively influences healthcare professionals' BI to adopt DT	0.055	2.021	0.023	Accepted
H7: Relative Advantage (RA) positively influences healthcare professionals' BI to adopt DT	0.067	2.372	0.009	Accepted
H8: Compatibility (COM) positively influences healthcare professionals' BI to adopt DT	0.165	5.128	0.000	Accepted
H9: Complexity (CLX) negatively influences healthcare professionals' BI to adopt DT	-0.064	2.867	0.002	Accepted
H10: Organizational Readiness (OR) positively influences healthcare professionals' BI to adopt DT	0.107	4.72	0.000	Accepted
H11: Higher Authority Support (HAS) positively influences healthcare professionals' BI to adopt DT	0.051	1.808	0.037	Accepted
H12: Regulatory Support (RS) positively influences healthcare professionals' BI to adopt DT	0.188	5.045	0.000	Accepted
H13: Behavioral Intention (BI) positively influences actual adoption and use of DT in healthcare	0.278	6.514	0.000	Accepted

($\beta = 0.107$, $p < 0.001$) and relative advantage ($\beta = 0.067$, $p = 0.009$) had also significant effects on user intention. Meanwhile, higher authority support ($\beta = 0.051$, $p = 0.037$) showed a weaker yet significant influence and as expected, complexity ($\beta = -0.064$, $p = 0.002$) had a significant negative effect, confirming that perceived difficulty of use reduces behavioral intention.

Finally, behavioral intention strongly predicted actual DT adoption behavior ($\beta = 0.278$, $p < 0.001$), validating its role as a direct precursor to DT use in healthcare.

We also analyzed the impact of control variables on DT adoption. Among them, education level ($\beta = 0.095$, $p < 0.05$), and professional experience ($\beta = -0.091$, $p < 0.05$), demonstrated a somewhat significant effect on

DT adoption. These results suggest that professionals with higher educational qualifications are marginally more inclined to adopt DT systems but more experienced professionals are less likely to adopt DT as indicated by the negative β value. Age ($\beta = -0.035$, $p = 0.239$), gender ($\beta = -0.003$, $p = 0.447$), and institution type ($\beta = 0.011$, $p = 0.326$) were found to be statistically non-significant. Table 6 includes the results of the control variables.

Goodness of Fit: R^2 and predictive relevance Q^2

We tested the structural model's predictive abilities through R^2 values of the endogenous constructs, as it shows the model's predictive power (Chin, 1998). Results with R^2 values of 0.19, 0.33, and 0.67 suggest weak, moderate, and good predictive capacity, respectively, as stated by Chin (1998). To further verify the predictive power of our model, we employed Stone-Geisser's Q^2. Q^2 values of 0.02, 0.15, and 0.35 indicate that the endogenous variable is minor, medium, or largely predictive, respectively (Henseler et al., 2016). But the model would be significant if $Q^2 > 0$ (Hair et al., 2017).

In our study, BI has a remarkably high R^2 value of 0.884, meaning that the combined UTAUT2 and TOE components account for 88.4% of the variance in BI. This shows that the predictors robustly explain what motivates healthcare professionals to embrace Digital Twin technology, indicating a powerful model fit. This is further supported by the model's high prediction accuracy for BI, which is confirmed by the Q^2 value of 0.873. DT Adoption (actual usage), on the other hand, has a comparatively low R^2 value of 0.085, meaning that behavioral intention alone accounts for just 8.5% of the variance in actual adoption. This is not uncommon in studies on technology adoption because real-world usage behavior is frequently impacted by institutional or external factors that cannot be predicted, such as technological restrictions, administrative regulations, or financial restraints (Ganesh, 2025; Hussain et al., 2023). Even yet, the DA's small Q^2 value of 0.084 indicates some predictive relevance, indicating that it still has a weak but significant predictive potential for actual DT adoption. These values are shown in Table 7.

We also measured the effect size, F^2 and a latent construct's effect size is classified as small, medium, or high if it ranges between 0.02 and 0.15 and 0.35, respectively (Cohen, 2013). Table 8 includes the F^2 values of all constructs. The majority of factors had small but significant effects on BI to adopt DT technology. With a medium effect ($f^2 = 0.162$), RS had the biggest influence among them, underscoring the crucial role that legal and regulatory frameworks play in influencing adoption. Relatively strong small effects were also shown by COM, EE, and FC, highlighting the significance of support infrastructure, system alignment, and ease of use. While SI, PFV, RA, and HAS exhibited small but statistically significant effect sizes, other variables such as had minimal effects. The path from behavioral intention to DT adoption also yielded a small effect ($f^2 = 0.081$), meaning that there might be some other unmodeled predictors of actual adoption along with BI.

Test of linearity

Following previous studies (Alam et al., 2021; Barua & Barua, 2023) to verify that the endogenous and exogenous variables were positively and significantly related to one another, we employed analysis of variance (ANOVA). Except for EE, all of the predictors had a linear and non-linear association with BI, as p-values are 0.000 for both linearity and divergence from linearity. EE is the only construct that has a strong and clean linear relationship with BI, but no nonlinear relationship is present between them ($p = 0.406$ for deviation from linearity). Not only that, but BI also has a linear and nonlinear relationship with DA. The results of the linearity test are presented in Table 9.

ANN analysis

SEM analysis has been utilized in plenty of studies for analyzing the causal relationship between various factors. However, the fact that SEM can only measure linear relationships suggests that it might not be the best tool to employ when making judgments about adopting new

Table 6 Control variables impact

Control variable	PLS path	Path coefficient (β value)	*P*-value	Result
Age	Age -> DT Adoption	− 0.035	0.239	Not Significant
Education level	Education -> DT Adoption	**0.095**	**0.024**	**Significant**
Gender	Gender -> DT Adoption	− 0.003	0.447	Not Significant
Professional experience	Professional Experience -> DT Adoption	**− 0.091**	**0.029**	**Significant**
Institution type	Institution Type -> DT Adoption	0.011	0.326	Not Significant

Table 7 Goodness of fit (R^2 and predictive relevance (Q^2))

Endogenous variables	*R*-square	Q^2predict
Behavioral intention	0.884	0.873
DT adoption	0.085	0.084

Table 8 Effect size

Path	f-square	Effect size
Performance Expectancy -> Behavioral Intention	0.028	small
Effort Expectancy -> Behavioral Intention	0.104	small
Social Influence -> Behavioral Intention	**0.011**	minimal
Facilitating Conditions -> Behavioral Intention	0.107	small
Price Value -> Behavioral Intention	0.025	small
Perceived Functional Value -> Behavioral Intention	**0.013**	minimal
Relative Advantage -> Behavioral Intention	**0.018**	minimal
Compatibility -> Behavioral Intention	0.117	small
Organizational Readiness -> Behavioral Intention	0.054	small
Complexity -> Behavioral Intention	0.024	small
Higher Authority Support -> Behavioral Intention	**0.012**	minimal
Regulatory Support -> Behavioral Intention	0.162	Medium
Behavioral Intention -> DT Adoption	0.081	small

Small, medium, and high effect sizes are represented, respectively, by $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$, according to (Cohen, 1988)

technologies (Priyadarshinee et al., 2017). Thus, numerous researchers proposed that combining ANN with SEM could address certain limitations of SEM, such as its limitation to analyze only linear correlations, which can lead to oversimplification of the complexities associated with human decision-making processes (Barua & Barua, 2023; Leong et al., 2015). We employed a multi-layer perceptron ANN in this study, a highly sequential computing processor made up of specialized processing units that have a neural inclination to store and render experimental data (Haykin & Network, 2004). An ANN's most basic building block is a neuron or node. The synaptic weights, or the weights of the integrated neurons, carry the acquired context information (Alam et al., 2021). In ANN analysis, synaptic weights would be controlled throughout learning to accomplish the goal outcome (Mustafa & Zhang, 2023). To create an output neuron node, hidden layer neurons learn to communicate with the input neurons predictably. An essential benefit of ANN is that it eliminates the need for multivariate assumptions, such as homoscedasticity and normality, which are necessary for statistical analysis (Leong et al., 2015).

For the ANN, we used SPSS 25. Multiple researchers had previously suggested using ten-fold cross-validation to avoid over-fitting (Sim et al., 2014). Ninety percent of the data was used for training, and the other 10% was used for testing. Previous research has shown that using a single hidden layer to represent continuous functions is sufficient and helpful (Barua & Barua, 2023; Sharma et al., 2016). Therefore, we follow this approach in our investigation. Furthermore, the Sigmoid function was employed as the activation function. The output and hidden layers also use this, and the Sigmoid function sets all parameters to a range of 0–1. The number was generated automatically since there was no set quantity of hidden neurones. Root mean square error (RMSE) measurements from ten networks were used to assess the model's accuracy. Table 10 displays the root-mean-squared errors (RMSEs) and standard error of judgements (SSEs) for these ten networks. The training and testing sets had maximum RMSE values of 0.066 and 0.068, respectively. So, ANN models are able to offer constant numerical correlations between predictors and outputs, as indicated by the RMSE values. (Fig. 2)

Sensitivity Analysis

The relative importance of the predictor variables was determined through the use of sensitivity analysis, which was also done in IBM SPSS 25. After determining each predictor's relative importance, we divided it by the

Table 9 Test of Linearity

			Sum of squares	df	Mean square	*F*	Sig
BI * PE	Between Groups	(Combined)	319.740	68	4.702	14.586	0.000
		Linearity	274.704	1	274.704	852.118	0.000
		Deviation from Linearity	45.036	67	0.672	2.085	0.000
	Within Groups		119.280	370	0.322		
BI * EE	Between Groups	(Combined)	311.641	88	3.541	9.731	0.000
		Linearity	278.869	1	278.869	766.253	0.000
		Deviation from Linearity	32.772	87	0.377	1.035	0.406
	Within Groups		127.378	350	0.364		
BI * SI	Between Groups	(Combined)	329.344	119	2.768	8.050	0.000
		Linearity	206.805	1	206.805	601.511	0.000
		Deviation from Linearity	122.540	118	1.038	3.020	0.000
	Within Groups		109.675	319	0.344		
BI * FC	Between Groups	(Combined)	340.313	102	3.336	11.357	0.000
		Linearity	274.258	1	274.258	933.586	0.000
		Deviation from Linearity	66.055	101	0.654	2.226	0.000
	Within Groups		98.706	336	0.294		
BI * PV	Between Groups	(Combined)	334.290	111	3.012	9.403	0.000
		Linearity	212.566	1	212.566	663.704	0.000
		Deviation from Linearity	121.724	110	1.107	3.455	0.000
	Within Groups		104.729	327	0.320		
BI * PFV	Between Groups	(Combined)	228.201	34	6.712	12.862	0.000
		Linearity	195.907	1	195.907	375.425	0.000
		Deviation from Linearity	32.293	33	0.979	1.875	0.003
	Within Groups		210.819	404	0.522		
BI * RA	Between Groups	(Combined)	307.862	95	3.241	8.475	0.000
		Linearity	213.742	1	213.742	558.975	0.000
		Deviation from Linearity	94.120	94	1.001	2.619	0.000
	Within Groups		131.157	343	0.382		
BI * COM	Between Groups	(Combined)	276.515	62	4.460	10.319	0.000
		Linearity	233.201	1	233.201	539.577	0.000
		Deviation from Linearity	43.314	61	0.710	1.643	0.003
	Within Groups		162.504	376	0.432		
BI * CLX	Between Groups	(Combined)	191.868	98	1.958	2.693	0.000
		Linearity	73.961	1	73.961	101.747	0.000
		Deviation from Linearity	117.906	97	1.216	1.672	0.000
	Within Groups		247.152	340	0.727		
BI * OR	Between Groups	(Combined)	314.699	107	2.941	7.831	0.000
		Linearity	200.257	1	200.257	533.180	0.000
		Deviation from Linearity	114.441	106	1.080	2.875	0.000
	Within Groups		124.321	331	0.376		
BI * HAS	Between Groups	(Combined)	258.297	101	2.557	4.769	0.000
		Linearity	156.928	1	156.928	292.629	0.000
		Deviation from Linearity	101.370	100	1.014	1.890	0.000
	Within Groups		180.722	337	0.536		
BI * RS	Between Groups	(Combined)	253.108	43	5.886	12.506	0.000
		Linearity	212.567	1	212.567	451.635	0.000
		Deviation from Linearity	40.541	42	0.965	2.051	0.000
	Within Groups		185.911	395	0.471		

Table 9 continued

			Sum of squares	df	Mean square	*F*	Sig
BI * DA	Between Groups	(Combined)	291.758	146	1.998	3.962	0.000
		Linearity	33.915	1	33.915	67.249	0.000
		Deviation from Linearity	257.843	145	1.778	3.526	0.000
	Within Groups		147.261	292	0.504		

Table 10 RMSE values

	Training			Testing			
Network	sample size, N	Sum of square error, SSE	RMSE	sample size, N	Sum of square error, SSE	RMSE	Total sample size
1	390	1.223	0.056	49	0.181	0.061	439
2	396	1.320	0.058	43	0.179	0.065	439
3	393	1.278	0.057	46	0.202	0.066	439
4	382	0.976	0.051	57	0.207	0.060	439
5	386	1.175	0.055	53	0.248	0.068	439
6	398	1.353	0.058	41	0.139	0.058	439
7	389	1.449	0.061	50	0.137	0.052	439
8	395	1.216	0.055	44	0.142	0.057	439
9	390	1.205	0.056	49	0.189	0.062	439
10	398	1.722	0.066	41	0.153	0.061	439
	Mean	1.2917	0.0572663	Mean	0.1777	0.0610805	
	SD	0.185983897	0.0038094	SD	0.03401485	0.0044372	

highest-valued predictor to get its normalized importance. Table 11 displays the percentage form of the result. The results shown in Table 11 indicate that RS (100%) is the strongest predictor of healthcare professionals' intention to implement DT technologies in healthcare organizations, followed by EE (96.29%), FC (91.99%), and CLX (80.86%).

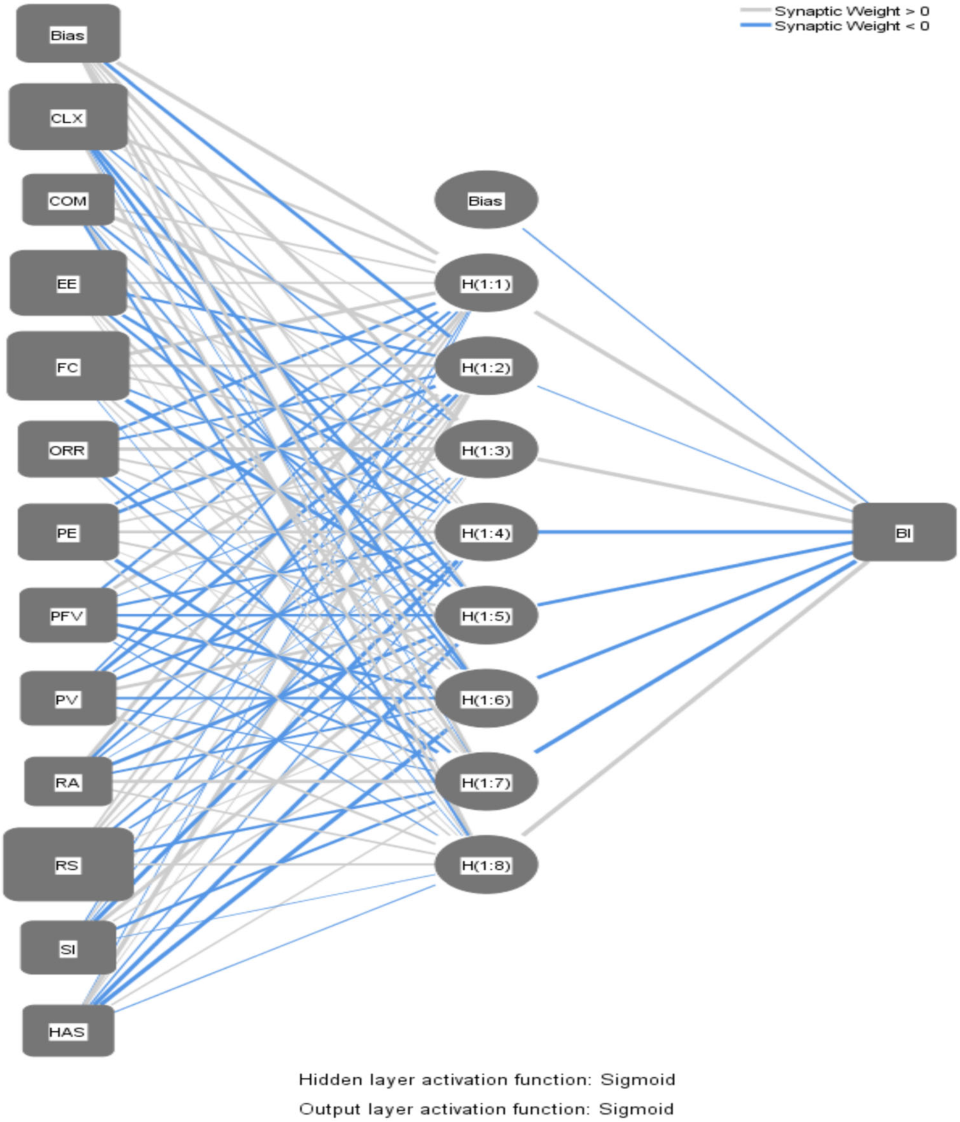
The final result of both SEM and ANN analysis is shown in Fig. 3.

Discussion and Implications

Based on the UTAUT2 and TOE frameworks, this study examined healthcare professionals' DT technology use intentions. Analyses used integrated SEM-ANN. The results reveal important personal and organizational factors affecting DT adoption.

The strongest UTAUT2 predictors were EE and FC. The results were significant ($\beta = 0.187$ and 0.188, respectively; $p < 0.05$) and had high normalized ANN importance (96.29% and 91.99%). It means that to promote DT, easy-to-use tools and support are needed. Both PE and PV were statistically significant ($\beta = 0.103$ and 0.082, respectively; $p < 0.05$), but their influence on ANN was only moderate (47.98% and 49.06%, respectively). Thus, when adopting DT, healthcare professionals consider its usefulness and value proposition. But they value technology usability more in high-stakes, time-sensitive settings like clinics and hospitals. PFV was statistically marginal but still significant with a lower normalized importance ($\beta = 0.055$, $p < 0.05$; ANN = 33.08%). This indicates that professionals are aware of the features of DT systems; however, this alone is insufficient to encourage their use unless the systems are both user-friendly and supported by institutions. Social influence (SI) was statistically significant but had a minimal effect ($\beta = 0.054$, $p < 0.05$; ANN = 28.94%), indicating that while peer or managerial endorsement may play a role, healthcare professionals' adoption decisions are primarily independent and internally motivated. Given that clinical technology adoption is often driven by formal institutional directives rather than social trends, this result is unsurprising. These findings are consistent with other technology adoption studies that utilized

Fig. 2 ANN diagram from SPSS



UTAUT2 models like 5G adoption (Mustafa et al., 2022a, 2022b), mobile health adoption (Barua & Barua, 2023), robot adoption in education (Suhail et al., 2024), and cryptocurrency adoption (Mishra et al., 2024).

From the TOE framework, RS was the most important predictor of DT adoption. SEM model showed statistical significance ($\beta = 0.188$, $p < 0.05$), and the ANN normalized importance was highest (100%). This highlights the importance of external compliance, regulatory frameworks, and institutional control in driving healthcare professionals' adoption of DT. This finding is consistent with other studies that implemented TOE framework for newer technology adoption i.e., blockchain adoption in supply chains (Chittipaka et al., 2023). COM significantly influenced BI, with a path coefficient of $\beta = 0.165$ ($p < 0.05$) and a high normalized importance of 80.86%. It indicates that DT systems are better accepted when they fit clinical procedures, IT infrastructure, and institutional routines. Healthcare compatibility extends beyond interoperability to encompass how well the technology integrates into existing care delivery patterns without causing operational friction. ORR ($\beta = 0.107$, $p < 0.05$; ANN = 50.65%) indicates that financially, technologically, and culturally competent organizations are more equipped to apply DT solutions. This involves trained staff, committed funds, and digital transformation plans. CLX resulted in a substantial negative correlation with behavioral intention ($\beta = -0.064$, $p < 0.05$) and moderate importance (35.22%). Complexity may overwhelm users and increase resistance, unlike compatibility, which promotes adoption when aligned with workflows. If the interface is unintuitive or poorly connected with existing systems, healthcare professionals may find DT technologies too complicated to understand. HAS and RA had the least effect among the

Table 11 Sensitivity Analysis

	Independent variable importance											
	Network 1	Network 2	Network 3	Network 4	Network 5	Network 6	Network 7	Network 8	Network 9	Network 10	Average	Normalized importance (%)
CLX	0.78	0.74	0.64	0.82	0.72	0.59	0.74	0.95	0.86	0.92	0.77	80.86
COM	0.29	0.30	0.42	0.39	0.34	0.37	0.63	0.20	0.31	0.13	0.34	35.22
EE	0.75	1.00	0.88	0.84	1.00	0.91	1.00	0.95	1.00	0.90	0.92	96.29
FC	0.86	0.78	0.95	0.94	0.83	1.00	0.86	0.96	0.80	0.85	0.88	91.99
ORR	0.44	0.40	0.44	0.48	0.54	0.49	0.45	0.61	0.46	0.52	0.49	50.65
PE	0.45	0.27	0.18	0.73	0.43	0.27	0.40	0.60	0.51	0.77	0.46	47.98
PFV	0.39	0.36	0.19	0.31	0.19	0.17	0.35	0.41	0.32	0.48	0.32	33.08
PV	0.36	0.48	0.50	0.45	0.39	0.45	0.52	0.44	0.42	0.68	0.47	49.06
RA	0.21	0.21	0.15	0.27	0.45	0.23	0.26	0.39	0.32	0.55	0.30	31.50
RS	1.00	0.91	1.00	1.00	0.89	0.77	1.00	1.00	1.00	1.00	0.96	100.00
SI	0.35	0.23	0.32	0.23	0.33	0.30	0.31	0.30	0.21	0.19	0.28	28.94
HAS	0.28	0.25	0.14	0.31	0.22	0.44	0.13	0.25	0.35	0.44	0.28	29.25

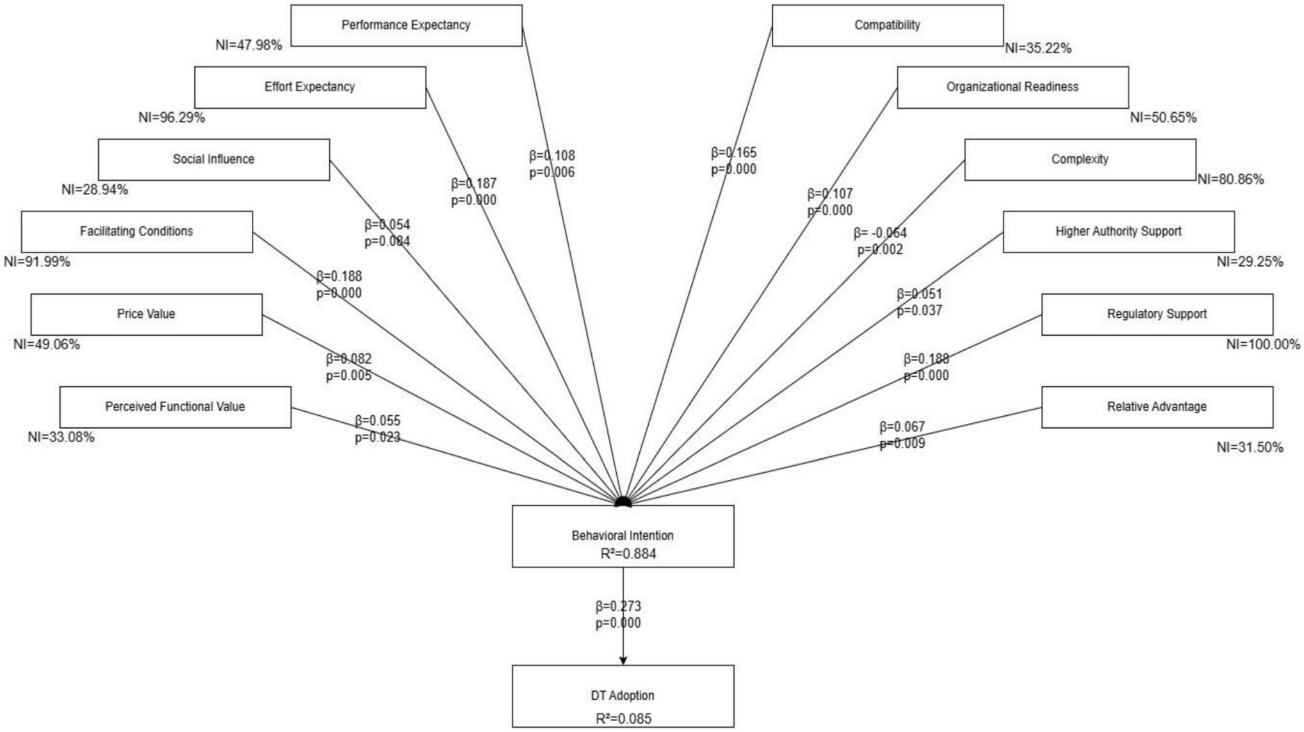


Fig. 3 Final result of SEM and ANN

TOE constructs on DT adoption, as seen by their lower normalized importance scores (29.25% and 31.5%, respectively). Even though both were statistically significant ($\beta = 0.051$ and $\beta = 0.067$, $p < 0.05$), the findings suggest that while leadership endorsements and perceived benefits over existing systems are important, they are not the main reasons the professionals adopt DT. All of these findings are consistent with numerous studies that focused on the TOE framework in technology adoption, such as blockchain adoption in supply chains (Chittipaka et al., 2023), cloud computing adoption in MSMEs (Aligarh et al., 2023; Al-Sharafi et al., 2023), AI in SMEs (Soomro et al., 2025), and big data adoption in sustainable marketing (Baig et al., 2023).

Furthermore, we found that BI has a positive and significant relationship ($\beta = 0.278$, $p < 0.05$) with DA. Many previous studies have already supported this result (Aligarh et al., 2023; Chittipaka et al., 2023; Mishra et al., 2024; Soomro et al., 2025). If users have a high intention to use or adopt a technology, they often end up using it. The model's robust prediction of BI ($R^2 = 0.884$, $Q^2 = 0.873$) shows that the UTAUT2 and TOE components have good explanatory and predictive power. However, the explained variation in actual DT adoption was minimal ($R^2 = 0.085$), which suggests that the combination of UTAUT2 and TOE framework may not be sufficient to analyze DA in healthcare settings. This finding is consistent with other studies that analyzed newer technology adoption in the surgical and healthcare environment (Ganesh, 2025; Hussain et al., 2023), as some unmodeled external or organizational variables can have a significant influence over DT adoption. However, DA's $Q^2 = 0.084$ indicates that the model still has some predictive value for actual usage.

Among the control variables, age ($\beta = -0.035$, $p = 0.239$), gender ($\beta = -0.003$, $p = 0.447$), and institution type ($\beta = 0.011$, $p = 0.326$) were not statistically significant. This implies that both younger and older healthcare professionals evaluate DT adoption similarly and technology adoption in terms of digital health is getting more gender neutral. Not only that, the healthcare professionals' response was independent of institution type. However, education level ($\beta = 0.095$, $p < 0.05$) and professional experience ($\beta = -0.091$, $p < 0.05$) showed a small association with DT adoption. This indicates that higher education is associated with a slightly greater likelihood of organizations adopting DT technologies. Also, professional experience having a negative association with DT adoption indicates that more experienced professionals are more hesitant toward integrating DT into their already established clinical workflows. This result shows that senior professionals may rely more on their experiential knowledge and they might be more comfortable with their current decision-making practices. So, addressing workflow redesign and incorporating new management strategies are important during DT adoption.

Theoretical Implications

By combining UTAUT2 and TOE two models frequently employed to explain technology adoption this study develops a model that is more contextually relevant and offers greater explanatory power in complex, regulated domains such as healthcare (Ates & Polat, 2025; Katebi & Tehrani, 2025).

Standalone models like UTAUT2 forecast consumer and voluntary adoption by focusing on individual-level factors such as performance expectancy, effort expectancy, and social influence. In contrast, the TOE framework considers contextual, organizational, and governance elements but does not account for behavioral motivations. This study addresses the limitations of both models by integrating UTAUT2 and TOE to develop a comprehensive framework that encompasses human and organizational factors as well as governance adherence, influencing digital transformation adoption. Regulatory support, higher authority support, and organizational readiness together reflect the governance systems that enable accountability, ethical compliance, and data stewardship in DT adoption in healthcare. The combined model explains 88.4% of the variance in behavioral intention, substantially more than either UTAUT2 or TOE alone in comparable contexts (Bouteraa, 2024). The findings contribute to theory by demonstrating that contextual TOE components, including regulatory support, compatibility, and organizational readiness, are equally if not more important than standard UTAUT2 predictors in the healthcare domain. This study also highlights how this integrated framework demonstrates flexibility through different constructs. Effort expectancy and facilitating conditions reflect usability-driven adaptability, compatibility analyzes the technological flexibility of the organization, organizational readiness embodies managerial adaptability, and regulatory support ensures flexibility in governance. Thus, we can see that management flexibility is a multidimensional outcome of these constructs.

Furthermore, we employed a two-stage hybrid SEM-ANN analytical methodology, which enhanced the methodological rigor of our model. While SEM enabled the evaluation of the significance of hypothesized relationships, ANN analysis ranked predictors based on normalized importance, capturing nonlinear relationships and offering deeper predictive insights. This dual approach not only confirms the significance of key constructs but also provides a ranked understanding of their practical influence an essential contribution to theory refinement. Importantly, our findings reveal that constructs such as social influence (SI) and relative advantage (RA), though statistically significant, are not as dominant as previously assumed. These factors did not rank highly enough to warrant prioritized attention in healthcare settings. Instead, the most critical determinants are practical considerations such as usability, institutional readiness, and regulatory support. This finding is particularly interesting since they highlight the importance of contextual boundaries in technology acceptance studies. Compliance and practicality will outweigh peer influence or novelty in highly regulated and risk-sensitive domain like healthcare. This particular type of domain also includes finance, aviation, etc. where practical considerations are more decisive. On the other hand, SI and RA could play central role in consumer-oriented contexts. This study also explains the cross-level mechanisms by which environmental and organizational factors influence individual behavioral intentions. Organizational readiness and compatibility act as enabling mechanisms as they influence individual perceptions of usability and complexity. When DT technologies integrate with current workflows and technical architectures, perceived complexity decreases. This, in turn, reinforces effect expectancy and performance expectancy. So, DT adoption is a nested, cross-level process in which governance structures create organizational readiness, which in turn influences individual cognitive evaluations, resulting in flexible managerial competence.

Practical Implications

Healthcare administrators, digital health vendors, legislators, and anyone else with a stake in implementing DT systems in healthcare organizations can benefit from the study’s several insightful empirical findings. Firstly, we found that complexity has an adverse effect on DT adoption, which means that doctors and nurses would be hesitant to employ systems that they think are too complicated or hard to use. System developers and hospital IT departments should prioritize usability, intuitive design, and hands-on training programs during the installation of DT technologies.

Secondly, the study indicated that the most important factors influencing adoption were regulatory support, effort expectancy, and facilitating conditions. All these three factors go hand in hand. This means that to gain healthcare professionals’ faith in DT systems, it is crucial to adhere to national healthcare regulations, data privacy standards, and medical safety measures. Government health agencies and regulatory bodies should establish clear, supportive frameworks for DT technologies and actively involve clinical professionals in shaping these guidelines. Moreover, hospitals must ensure the availability of technical support infrastructure, IT personnel, and training resources, which collectively form the facilitating conditions necessary for successful DT implementation. Thirdly, healthcare organizations should evaluate their digital maturity, financial allocation, and strategic alignment before implementing DT tools, as organizational readiness is ranked the fourth most important predictor for DT adoption. Our results indicate that higher authority support plays a pivotal role in ensuring all necessary systems are in place, although it has less influence on directly predicting user acceptance. Furthermore, compatibility is another key aspect of user acceptance as it is crucial to thoroughly evaluate how well it will integrate with pre-existing electronic systems and clinical tasks. More people will use DT solutions if they are easy to link with other systems, like as EHRs, diagnostic platforms, and hospital information systems.

Fourthly, factors with low importance scores, such as relative advantage, social influence, perceived functional value, and perceived value, cannot be overlooked since their roles remain statistically significant in the broader adoption process. These factors, while not the primary drivers of adoption, influence the perception, confidence, and sustained involvement with DT technologies. For instance, if we can effectively articulate the distinct benefits of DT compared to existing systems, it can augment perceived value over time, particularly when supported by real-world outcomes and success stories. Enhancing perceptions of value and functionality through user education, testing, and testimonials can increase their impact during subsequent adoption stages. Collectively, these factors with lower normalized scores represent leverage points for boosting DT adoption through targeted strategies.

Fifthly, healthcare officials should take this study’s results into account when they allocate funds for innovation or create national digital health plans. Public education on digital health safety, collaborations with medical colleges to build skills, and the creation of standardized DT frameworks can all help to increase adoption. To be at the forefront of data-driven healthcare transformation and precision medicine in the future, healthcare institutions must proactively invest in organizational support structures. Finally, the value of UTAUT2-TOE framework extends beyond DT adoption prediction as it serves as a guide for flexible managerial action. Since EE, PE, FC, RS, etc. constructs emerged as significant drivers, when DT is adopted into the system, managers will respond with adaptive training and simplified system interfaces by default. So, our proposed framework informs the managers and administrators about the adoption of DT, which in turn provides a practical approach to achieve flexible dimensions in every aspect of the organization.

Conclusion

This study presents a comprehensive examination of the adoption and utilization of digital transformation (DT) technologies by healthcare professionals within organizational contexts. The findings indicate that while individual-level factors such as effort expectancy (EE) and facilitating conditions (FC) significantly influence behavioral intention (BI), organizational and environmental factors, including regulatory support (RS) and system compatibility (COM), are equally pivotal. Although behavioral intention demonstrates strong predictive power, the limited variance explained in actual DT adoption (DA) suggests the influence of additional, unaccounted-for organizational dynamics. This study offers a more sophisticated perspective for scholars investigating complex healthcare technology ecosystems and underscores the importance of adopting a multifaceted approach in future studies. Our proposed framework encourages a more flexible approach in management so that DT can be integrated seamlessly. In resource-constrained environments like Bangladesh, this flexibility is particularly valuable, enabling organizations to balance innovation with operational stability while embedding digital twins into healthcare delivery.

Although we comprehensively examined the adoption of Digital Twin (DT) technology in the healthcare sector, this study is not without limitations. First, data were collected from a single country, Bangladesh, with most respondents based in the capital city, Dhaka. We recommend conducting similar studies across multiple countries to explore whether differences in cultural norms, policy environments, and healthcare infrastructure affect DT adoption behavior. Second, we did not analyze the moderating effects of demographic variables such as age, gender, education, or digital literacy. Future research should consider including these variables as moderators to better tailor implementation strategies to different user segments. Finally, our study identifies regulatory support as the most critical factor influencing DT adoption. Given that DT systems handle sensitive patient information, support clinical decision making, and require system-level integration, healthcare professionals are unlikely to adopt them without robust legal and ethical assurances. We encourage researchers to investigate existing regulatory standards and support mechanisms within healthcare organizations and to analyze how these frameworks must evolve to facilitate smoother DT adoption. Focusing on these areas would enhance the generalizability and practical significance of future research on DT implementation in healthcare.

Appendix A: Table for measurement construct

Construct	Items	Measurement item (Sample statement)	Source
Behavioral intention	BI1	I intend to use digital technology (DT) in the future	Mustafa et al. (2022a, 2022b), Venkatesh et al. (2012a)
	BI2	I will always try to use DT in my daily activities	
	BI3	I plan to continue using DT regularly	
DT adoption	DA1	I have adopted DT in my work	Alam et al. (2021)
	DA2	I use DT regularly	
	DA3	DT is integrated into my daily activities	
	DA4	I rely on DT for important tasks	
	DA5	DT is my preferred method for relevant tasks	
Compatibility	COM1	Using DT is compatible with my needs	Kim et al. (2007)
	COM2	DT fits well with my work style	
	COM3	DT is consistent with my values	
Complexity	CLX1	DT is complicated to use	Kim et al. (2007)
	CLX2	I find DT confusing	
	CLX3	Learning to use DT is difficult	
	CLX4	I need help to use DT	
Effort expectancy	EE1	Learning to use DT is easy for me	Mustafa et al. (2022a, 2022b), Venkatesh et al. (2012a)
	EE2	My interaction with DT is clear and understandable	
	EE3	I find DT easy to use	
	EE4	It is easy for me to become skillful at using DT	
Facilitating conditions	FC1	I have the resources necessary to use DT	Mustafa et al. (2022a, 2022b), Venkatesh et al. (2012a)
	FC2	I have the knowledge necessary to use DT	
	FC3	DT is compatible with other technologies I use	
	FC4	I can get help from others when I have difficulties using DT	
Organizational readiness	OR1	My organization is ready to adopt DT	Alam et al. (2021)
	OR2	There is support for DT in my organization	
	OR3	Sufficient infrastructure for DT exists	
	OR4	DT adoption is encouraged by management	
	OR5	My organization provides training for DT	

continued

Construct	Items	Measurement item (Sample statement)	Source
Perceived functional value	PFV1	DT offers valuable functions for my work	Kim et al. (2007)
	PFV2	DT enhances my performance	
Performance expectancy	PE1	Using DT will increase my productivity	Mustafa et al. (2022a, 2022b), Venkatesh et al. (2012a)
	PE2	DT will help me accomplish tasks more quickly	
	PE3	DT will improve my job performance	
Price value	PV1	DT is reasonably priced	Mustafa et al. (2022a, 2022b), Venkatesh et al. (2012a)
	PV2	DT is good value for the money	
	PV3	At the current price, DT provides good value	
Regulatory support	RS1	There is sufficient regulatory support for DT	Alam et al. (2021)
	RS2	Government policies favor DT adoption	
	RS3	DT is supported by relevant authorities including data privacy and ethical governance	
Relative advantage	RA1	DT is better than other available solutions	Kim et al. (2007)
	RA2	DT offers more advantages than alternatives	
	RA3	DT is superior to previous technologies	
	RA4	DT gives my organization a strategic advantage in healthcare delivery	
Social influence	SI1	People important to me think I should use DT	Mustafa et al. (2022a, 2022b), Venkatesh et al. (2012a)
	SI2	People who influence my behavior think I should use DT	
	SI3	People whose opinions I value prefer that I use DT	
Higher authority support	HAS1	Senior management supports DT adoption	Alam et al. (2021)
	HAS2	Leadership encourages DT use	
	HAS3	There is visible support from top management	
	HAS4	DT is a priority for higher authorities	

Appendix B: Table for instrument refinement summary

Item	Source	Feedback from experts panel	Revision made before final survey
Behavioral intention (BI1–BI3)	Mustafa et al., (2022a, 2022b); Venkatesh et al., (2012a)	Experts noted that the phrase "digital technology" was too generic; practitioners suggested specifying "Digital Twin (DT)" for clarity	Replaced "digital technology" with "DT" throughout; simplified sentence structure for readability
DT adoption (DA1–DA5)	Alam et al., (2021)	–	–
Compatibility (COM1–COM3)	Kim et al. (2007), Alkhater et al. (2018)	Suggested aligning terminology with healthcare workflows	Modified items to refer to DT in clinical or managerial workflows for contextual relevance
Complexity (CLX1–CLX4)	Kim et al. (2007), Alkhater et al. (2018)	Some items were double negatives and confusing during pilot testing	Simplified phrasing such as, "DT is complicated to use" instead of "DT is not easy to use"
Effort expectancy (EE1–EE4)	Mustafa et al.,(2022a, 2022b), Venkatesh et al., (2012a)	Participants found "interaction with DT" ambiguous	Clarified EE2 to "My interaction with DT systems is clear and understandable."
Facilitating conditions (FC1–FC4)	Mustafa et al., (2022a, 2022b), Venkatesh et al., (2012a)	Healthcare professionals asked to include support from peers, not only technical help	Added "I can get help from others when I have difficulties using DT."

continued

Item	Source	Feedback from experts panel	Revision made before final survey
Organizational readiness (OR1–OR5)	Alam et al., (2021), Aligarh et al. (2023)	Reviewers emphasized including management training and support	Added OR5: "My organization provides training for DT."
Perceived functional value (PFV1–PFV2)	Kim et al. (2007), Mustafa et al., (2022a, 2022b)	–	–
Performance expectancy (PE1–PE3)	Mustafa et al., (2022a, 2022b), Venkatesh et al., (2012a)	Items overlapped with PFV; requested distinction between value and performance	Clarified wording to focus on productivity, efficiency, and job performance
Price Value (PV1–PV3)	Mustafa et al., (2022a, 2022b), Venkatesh et al., (2012a)	–	–
Regulatory support (RS1–RS3)	Alam et al., (2021), Alkhater et al. (2018)	Experts emphasized data privacy and ethical oversight	Added phrase "including data privacy and ethical governance" in RS3
Relative advantage (RA1–RA4)	Kim et al. (2007), Alkhater et al. (2018)	Practitioners found "competitive advantage" confusing in public-sector healthcare	Modified RA4 to "DT gives my organization a strategic advantage in healthcare delivery."
Social influence (SI1–SI3)	Mustafa et al., (2022a, 2022b), Venkatesh et al., (2012a)	–	–
Higher authority support (HAS1–HAS4)	Alam et al., (2021), Alkhater et al. (2018)	Reviewers wanted stronger emphasis on leadership and managerial visibility	Revised HAS3 and HAS4 to include visible leadership commitment and policy prioritization

Author Contributions All authors made significant contributions to this study. The conception and design of the research framework were jointly developed, with particular emphasis on the integration of the UTAUT2 and TOE models. Data collection, survey instrument development, and pilot testing were collaboratively undertaken to ensure methodological rigor and contextual validity. Statistical analyses, including SEM and ANN, were performed with shared input, and the interpretation of findings was collectively discussed and refined. The lead author prepared the initial draft of the manuscript, while the second and corresponding author provided critical revisions, intellectual enrichment, and refinement of both the theoretical and practical implications. In addition, the second and corresponding author supervised the overall project. All authors thoroughly reviewed the manuscript, approved the final version, and agree to be accountable for all aspects of the work.

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Declarations

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Key Questions

1. Does integrating UTAUT2 and TOE provide a more accurate explanation of Digital Twin adoption than applying either model independently in regulated healthcare contexts?
2. How does the integration of SEM with ANN modeling reshape our understanding of linear versus nonlinear relationships in digital transformation research?
3. Which adoption factors are more important for adopting Digital Twin in healthcare?

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