Digital Twins in Healthcare: Exploring the Drivers of Adoption and Value Creation

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Abstract

Healthcare systems face mounting pressure from demographic ageing, rising chronic disease prevalence, workforce constraints, and escalating costs. Digital Twins (DTs) have emerged as a promising digital innovation, enabling high-fidelity virtual representations of patients and hospital systems for simulation, prediction, and optimisation. Despite technological progress and growing investment, DT adoption in healthcare remains largely confined to isolated pilot projects.

This dissertation examined why DTs struggle to scale beyond experimentation and investigates the key drivers shaping their adoption and value creation in healthcare. It adopted an exploratory sequential mixed-methods design, integrating a literature review, twelve semi-structured expert interviews with healthcare and digital health stakeholders, and a healthcare consumer survey. The analysis was grounded in the Technology Acceptance Model (TAM), the Technology–Organization–Environment (TOE) framework, and Dynamic Capabilities Theory.

The findings showed that DT adoption is primarily driven by technological readiness and organisational integration. Particularly data interoperability, workflow alignment, governance structures, and leadership commitment. Individual attitudes such as trust, openness, and risk perception do not function as primary drivers but mediate how organisational capabilities translate into adoption. Survey results further indicated that perceived usefulness is context-dependent and shaped by health experience and dissatisfaction with existing healthcare systems.

Overall, the study reframes DT adoption as an organisational transformation challenge and concludes that scalable implementation depends on institutional capability alignment rather than incremental gains in individual user acceptance.

Keywords: Digital Twins, Healthcare Innovation, Technology Adoption, Digital Health

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Resumo

Os sistemas de saúde enfrentam pressões crescentes decorrentes do envelhecimento demográfico, do aumento das doenças crónicas, de restrições na força de trabalho e do crescimento dos custos. Os Gémeos Digitais (*Digital Twins*, DTs) surgem como uma inovação digital promissora, permitindo simulação, previsão e optimização de pacientes e sistemas hospitalares. No entanto, a sua adoção permanece maioritariamente limitada a projetos-piloto.

Esta dissertação investiga os fatores que condicionam a adoção e a criação de valor dos DTs na saúde. O estudo adota um desenho de métodos mistos sequenciais exploratórios, combinando revisão da literatura, entrevistas semiestruturadas com profissionais da saúde e da saúde digital, e um inquérito a consumidores. A análise baseia-se no Modelo de Aceitação da Tecnologia (TAM), no enquadramento Tecnologia–Organização–Ambiente (TOE) e na Teoria das Capacidades Dinâmicas.

Os resultados demonstram que a adoção de DTs é sobretudo determinada pela prontidão tecnológica e pela integração organizacional, em particular pela interoperabilidade dos dados, governação e liderança. As atitudes individuais atuam como fatores mediadores. Globalmente, o estudo conclui que a adoção escalável de DTs depende do alinhamento das capacidades institucionais.

Palavras-chave: Gémeos Digitais; Inovação em Saúde; Adoção de Tecnologia; Capacidades Dinâmicas; Saúde Digital

Título: Gémeos Digitais na Saúde: Exploração dos Fatores de Adoção e Criação de Valor
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Finally, I would like to state that selected AI-supported tools were used in a supportive capacity, particularly for language refinement, structuring of text passages, and the summarisation of interview material. The conceptual development, analysis, interpretation, and full responsibility for the content of this thesis remain entirely with the author.

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List of Abbreviations

AI	Artificial Intelligence
ANOVA	Analysis of Variance
ANCOVA	Analysis of Covariance
BIM	Building Information Modelling
DT	Digital Twin
DOI	Diffusion of Innovation Theory
GDPR	General Data Protection Regulation
ICT	Information and Communication Technology
IoMT	Internet of Medical Things
MDR	Medical Device Regulation
MDT	Medical Digital Twin
OECD	Organisation for Economic Co-operation and Development
PACS	Picture Archiving and Communication System
PDF	Portable Document Format
PLM	Product Lifecycle Management
RBV	Resource-Based View
RIS	Radiology Information System
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TOE	Technology–Organization–Environment
VBHC	Value-Based Healthcare

1 Introduction

1.1 Background and Motivation

Healthcare systems are facing intensifying structural pressures that challenge their long-term viability. Demographic ageing is a central driver of these pressures. By 2050, more than one quarter of the global population is expected to be aged 65 or older. This demographic shift increases the prevalence of chronic and multi-morbid conditions and places sustained strain on hospital capacity, workflows, and workforce availability (OECD, 2025).

In this context, digital innovation has shifted from a strategic option to an operational necessity. Among emerging technologies, Digital Twins (DTs) have attracted attention. They combine real-time data integration, simulation, and predictive analytics to support integrated clinical and operational decision-making (Grieves, 2014). Originating in aerospace engineering and later applied in manufacturing, DTs are increasingly being translated into healthcare contexts (Glaessgen & Stargel, 2012).

In healthcare, Medical Digital Twins (MDTs) integrate multi-modal patient and organisational data to support personalised treatment planning, risk prediction, and hospital-wide coordination (Sadée et al., 2025). The DT market is projected to grow from US$4.47 billion in 2025 to approximately US$59.94 billion by 2030. Despite this rapid expansion, adoption in routine hospital practice remains uneven and largely under (MarketsandMarkets, 2025). Beyond individual clinical use cases, DTs are increasingly discussed as system-level tools for improving patient flow, resource allocation, and operational resilience (Han et al., 2023).

1.2 Problem Statement

Despite their conceptual and technological promise, DTs have yet to achieve routine adoption in healthcare. Most implementations remain confined to isolated pilots within highly digitalised institutions, indicating that the primary challenge lies not in technological feasibility but in the conditions required for institutionalisation.

Implementing a DT demands the alignment of interoperable data infrastructures, clinical workflows, and governance arrangements under sustained leadership commitment. These requirements frequently exceed existing organisational capacities, while adoption efforts often prioritise technical performance over socio-technical and managerial integration (Brommeyer et al., 2023; Kuriakose et al., 2024).

The problem this thesis addresses, therefore, is not whether DTs could transform healthcare, but why their adoption remains limited and which factors determine whether adoption becomes feasible in real-world hospital environments.

1.3 Research Gap and Relevance

Although academic interest in healthcare DTs has increased, existing research provides only a partial understanding of adoption. Most studies focus on technical architectures, modelling approaches, or isolated clinical use cases, while empirical analyses of adoption processes within hospital organisations remain scarce.

This gap is particularly relevant because DTs differ fundamentally from many other digital health technologies. DTs rely on continuous synchronisation, multi-modal data integration, and cross-functional collaboration. This creates a level of socio-technical complexity that cannot be fully explained by technology-centred adoption perspectives.

From a theoretical perspective, this thesis extends established technology adoption frameworks by conceptualising DT adoption not as a static acceptance decision but as a capability-building process. While models such as TAM and TOE explain individual and organisational adoption conditions, they offer limited insight into how hospitals develop and sustain the capabilities required to institutionalise complex technologies. Integrating the Resource-Based Theory and Dynamic Capabilities addresses this limitation.

From a practical perspective, hospital managers, policymakers, and technology providers require clearer evidence on the conditions under which DTs can progress beyond pilot projects and become embedded in routine clinical and operational practice.

1.4 Research Question and Objectives

To address this gap, this thesis investigates the **Research Question**:

What are key factors driving adoption of Digital Twins in healthcare?

The objective of this thesis is to explain DT adoption as a multi-level phenomenon by integrating theoretical insights with empirical evidence from professional stakeholders and healthcare consumers. Specifically, the thesis aims to:

- Identify the technological, organisational, individual, and environmental determinants of DT adoption discussed in the literature.

- Examine how these determinants manifest in practice through expert perspectives from clinical, managerial, consulting, MedTech, and academic contexts.
- Assess individual-level attitudes, including perceived usefulness, trust, risk perception, and openness, through a healthcare consumer survey.
- Synthesize findings into a triangulated adoption framework and derive actionable implications for hospital leaders, policymakers, and technology providers.

Rather than isolating single causal effects, this thesis aims to identify and structure the interdependent conditions under which DT adoption becomes feasible in hospital contexts.

1.5 Structure of the Thesis

The thesis is structured into six chapters. Chapter 1 introduces the research context, problem statement, research gap, and objectives of the thesis. Chapter 2 provides a structured review of the conceptual foundations of DTs, their applications in healthcare, and relevant technology adoption theories, culminating in the development of an Adoption Driver Framework.

Chapter 3 outlines the exploratory mixed-methods research design and methodological approach. Chapter 4 presents the empirical findings derived from the literature review, expert interviews, and healthcare consumer survey. Chapter 5 synthesises these findings into a hierarchical adoption model. Chapter 6 concludes the thesis by summarising the key contributions, outlining limitations, and suggesting directions for future research.

2 Literature Review

2.1 Origins and Definitions of Digital Twins

The concept of the Digital Twin originated in aerospace engineering, where virtual counterparts of spacecraft were used to simulate operations and support decision-making under real conditions. NASA applied this approach in the 1960s and 1970s, notably during the Apollo 13 mission, where engineers relied on ground-based simulators to reproduce system malfunctions and identify corrective procedures (Glaessgen & Stargel, 2012).

The term *Digital Twin* was introduced in 2003 by Grieves in the context of *Product Lifecycle Management (PLM)*. He defined it as a digital representation of a physical product that remains continuously linked to its real-world counterpart through bidirectional data flows across its lifecycle (Grieves, 2014). The concept was subsequently integrated into Industry 4.0 initiatives, where it has been described as a foundational element for data-driven optimisation across product lifecycles (Qi et al., 2021; Tao et al., 2019).

The theoretical understanding of digital twins was further refined by introducing a reference model that distinguishes five domains: physical, virtual, data, connection, and service (Tao et al., 2019). This model represents the progression from static, descriptive modelling toward adaptive, data-driven systems capable of continuous learning and interaction between the physical and digital layers.

In healthcare, the DT concept has recently been adapted under the term Medical Digital Twin (MDT), which applies similar principles to biological and clinical contexts.

As stated by Sadée et al. (2025):

> *medical digital twins combine diverse health data streams and disease modelling to produce a dynamic copy of a patient that guides the clinical team towards personalised treatment* (p. 1).

A Medical Twin consists of five layers:

1. **The patient** – the physical entity represented through multimodal clinical data.
2. **Data connection** – interoperable pipelines that integrate and transfer patient data to the digital model.
3. **Patient-in-silico** – a computational model that simulates biological processes and treatment responses.
4. **Interface** – clinician-facing tools that translate model outputs into actionable insights.
5. **Synchronisation** – continuous updating of the model as new clinical data become available.

By combining mechanistic modelling with AI-based learning, MDTs enable simulation, prediction, and ongoing adaptation of medical interventions. This extension illustrates how an engineering-based concept has been translated into a data-driven approach to individualised clinical care (Sadée et al., 2025).

Building on these definitions and conceptual foundations, the next section reviews how the DT paradigm is being applied in healthcare practice.

2.2 Applications of Digital Twins in Healthcare

DT technologies are applied across multiple layers of the healthcare delivery system and contribute to value creation in different ways. To structure this heterogeneous body of research, this section adopts Porter and Teisberg’s Value-Based Healthcare (VBHC) perspective, which conceptualises value as the relationship between health outcomes and the resources required to achieve them (Porter & Teisberg, 2006).

Accordingly, DT applications are organised into three interlinked layers: clinical applications that directly affect patient outcomes; clinical-administrative applications that shape the coordination and organisation of care delivery; and administrative-support applications that stabilise hospitals' infrastructural and operational foundations. This classification does not introduce new theoretical categories but systematises recurring patterns in the existing Digital Twin literature, thereby providing conceptual clarity on how DTs contribute to value creation across the care delivery chain (Porter & Lee, 2013; Porter & Teisberg, 2006).

2.2.1 Clinical Applications

Clinical applications represent the most patient-facing DT use cases and directly support diagnosis, therapy, and ongoing monitoring.

2.2.1.1 Modelling and Diagnostic Digital Twins

DTs enhance diagnostic capabilities by creating computational representations of organs, physiological subsystems, and disease processes (Sadée et al., 2025). **Cardiology** offers well-established examples. Virtual cardiac models simulate haemodynamic behaviour, electrophysiology, and tissue mechanics. Clinicians can use these simulations to explore alternative diagnostic scenarios and improve assessments of cardiovascular disease severity (Erol et al., 2020).

Comparable approaches are found in **metabolic medicine**, where DTs of glucose–insulin dynamics forecast glycaemic excursions and identify deviations from expected physiological patterns (Sadée et al., 2025). Across these domains, modelling-based DTs transform raw clinical data into decision-supporting insights, thereby enhancing diagnostic accuracy and risk stratification.

2.2.1.2 Therapeutic and Interventional Digital Twins

Therapeutic and interventional DTs support clinical decision-making by enabling virtual simulation and optimisation of treatment strategies. In surgical and orthopaedic contexts, patient-specific anatomical and biomechanical models allow preoperative rehearsal of procedures and intervention planning. These models simulate anatomical structures, stress distributions, and implant performance, thereby reducing uncertainty and improving procedural preparedness (Sun et al., 2023).

In oncology, tumour-specific DTs integrate imaging, genomic, and biomarker data. These models are used to predict treatment response and potential resistance pathways, thereby supporting more personalised therapy selection (Sadée et al., 2025). These applications extend the role of DTs from descriptive modelling toward predictive and evaluative decision support in clinical interventions.

2.2.1.3 Monitoring and Adaptive-Care Digital Twins

A defining feature of DTs is their capacity for continuous synchronisation with patient data. By linking real-time bio signals, clinical measurements, and behavioural information, DTs support dynamic patient monitoring and adaptive clinical management.

In **cardiology**, DTs process ECG data to detect early arrhythmic deviations, prompting timely intervention (Erol et al., 2020; Sadée et al., 2025). In **metabolic care**, they predict glucose fluctuations to mitigate acute risk events (Sadée et al., 2025). This continuous learning cycle shifts care from episodic interventions to ongoing adaptive management and improves longitudinal outcome stability.

From a Value-Based Healthcare perspective, clinical DTs create value by improving patient outcomes without proportionally increasing resource use. By supporting earlier intervention, complication prevention, and sustained treatment effectiveness, they contribute directly to primary clinical value creation (Porter & Lee, 2013; Porter & Teisberg, 2006).

2.2.2 Clinical-Administrative Applications

Clinical-administrative applications operate at the interface between clinical practice and operational management. They do not deliver direct therapeutic effects. Instead, they influence the efficiency, reliability, and coordination of care delivery, which the Value-Based Healthcare framework links to outcomes and costs (Porter & Lee, 2013).

2.2.2.1 Patient Flow and Care Pathway Simulation

Hospitals must manage dynamic patient volumes and complex interdependencies. Digital-Twin-based simulations of patient flow identify bottlenecks, reduce waiting times, and improve cross-departmental coordination. By modelling capacity constraints and throughput patterns, these simulations enable data-driven planning and increase operational responsiveness (Erol et al., 2020; Han et al., 2023; Vallée, 2023).

2.2.2.2 Surgical Workflow and Resource Allocation

Surgical environments are characterised by high resource intensity and temporal sensitivity. DTs are used to model multi-resource scheduling constraints, including staff availability, equipment requirements, and operating-room turnover. This reduces idle time, anticipates conflicts, and improves procedure sequencing (Han et al., 2023).

Advanced surgical DTs further reconstruct operating theatres in virtual environments to optimise layout and workflow configurations. By integrating patient-specific, organisational, and procedural data, these systems support comprehensive preoperative and intraoperative decision-making (Kleinbeck et al., 2024).

2.2.2.3 Capacity and Demand Management

DTs support real-time demand forecasting and resource allocation across hospitals. Typical applications include modelling bed occupancy, predicting length of stay, and planning discharge flows. These capabilities improve cross-departmental coordination and reduce operational variability (Erol et al., 2020; Han et al., 2023).

From a Value-Based Healthcare perspective, clinical-administrative DTs create value by reducing process inefficiencies such as waiting times, extended length of stay, and unplanned cancellations. By improving pathway reliability and aligning capacity with demand, they lower operational costs while indirectly supporting stable clinical outcomes (Han et al., 2023; Porter & Lee, 2013; Porter & Teisberg, 2006).

2.2.3 Administrative and Support Applications

Administrative-support applications strengthen the infrastructural and organisational foundations of care delivery. While they do not directly affect clinical outcomes, they influence the structural cost base and operational continuity of hospitals (Brommeyer et al., 2023; Porter & Lee, 2013).

2.2.3.1 Logistics and Supply Chain Digital Twins

DTs integrate procurement, inventory, and distribution data to enable real-time monitoring and optimisation of hospital supply chains. These models increase transparency, anticipate shortages, and simulate disruption scenarios, thereby enhancing resilience and reducing waste (Han et al., 2023).

2.2.3.2 Facility and Infrastructure Digital Twins

Facility-level DTs combine BIM and IoT data to monitor and optimise environmental and technical systems, such as ventilation, lighting, and medical gas supply. By enabling anomaly detection and predictive maintenance, they reduce downtime and support operational continuity (Han et al., 2023).

2.2.3.3 Workforce and Staffing Simulation

Although less prevalent in healthcare research, workforce-oriented DTs are used to model staffing needs, workload distribution, and shift planning. Conceptual frameworks from other sectors suggest that DT-based workforce simulations can be adapted to hospital settings, while early industry implementations link staffing models to capacity and demand forecasting (Lu et al., 2020).

Within the Value-Based Healthcare framework, support functions such as logistics, infrastructure, and workforce deployment are structural determinants of healthcare costs (Porter & Teisberg, 2006). Administrative-support DTs reduce inefficiencies by lowering stockout frequency, minimising equipment downtime, and improving labour utilisation, thereby supporting cost control and operational reliability (Han et al., 2023).

2.2.4 Enabling Capabilities

DTs depend on robust enabling capabilities. Interoperability across systems, data availability, and information and communication technology (ICT) readiness are essential to ensure bidirectional synchronisation and coordinated decision-making, as consistently highlighted in the literature (Sadée et al., 2025).

Cybersecurity-focused DTs represent an emerging research domain. By creating virtual replicas of hospital networks and IoMT ecosystems, these systems support attack simulation, anomaly detection, and predictive threat modelling, thereby strengthening the resilience of DT-enabled infrastructures (Airehenbuwa et al., 2025).

2.3 Technology Adoption in Healthcare

2.3.1 Disruptive Innovation Theory: The Case for Digital Twins

In recent years, digital twins have often been portrayed as a *"truly disruptive innovation"* in healthcare (Kuriakose et al., 2024). They are praised for their potential to simulate patient physiology, optimize hospital operations, and shift care delivery from reactive to predictive modes.

The concept of disruption, however, has a specific meaning. Since Clayton Christensen's seminal work, disruption has referred to a distinct process by which new entrants challenge incumbents through initially inferior, but more accessible, products that eventually reshape entire value networks (Christensen, 2008; Christensen et al., 2009). In healthcare, disruption denotes technological change that enables simpler, lower-cost, and more decentralized models of care (Christensen et al., 2009).

Disruptive innovations differ from sustaining ones in that the latter improve existing products or processes within established markets, while disruptive innovations emerge at the periphery, targeting underserved or new user segments before gradually displacing incumbents. In the context of DTs, this framework indicates mixed evidence. Current applications are concentrated in resource-intensive institutions, where DTs are used to enhance precision medicine and intensive care. These implementations build on existing infrastructures rather than redefining care delivery (Yu & Hang, 2010).

For this thesis, the Disruptive Innovation framework serves as a conceptual reference point rather than a primary explanatory. DT adoption in healthcare is more likely to unfold through incremental institutional integration than through disruptive market displacement.

The following sections accordingly introduce the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework to analyse adoption across individual, organisational, and environmental levels.

2.3.2 Technology Adoption Models for Hospitals

Understanding why digital innovations succeed in healthcare while others fail to become institutionalised requires theoretical models that explain how adoption decisions emerge. This is particularly relevant for DTs, whose integration depends on both individual acceptance and organisational readiness.

To capture these dimensions, this thesis applies two complementary frameworks widely used in digital health research: the Technology Acceptance Model (TAM) (Davis, 1989) and the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990). Together, they provide a multilevel analytical structure encompassing individual, organisational, and environmental determinants of adoption.

The ***Technology Acceptance Model*** conceptualises adoption at the individual level. It posits that behavioural intention is shaped by perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which a technology enhances performance, while perceived ease of use reflects the effort required to operate it (Davis, 1989). These perceptions influence attitudes toward use and ultimately determine acceptance (Holden & Karsh, 2010; Marangunić & Granić, 2015).

Healthcare settings are characterised by high cognitive demands, time pressure, and strong workflow dependency. In such environments, TAM has proven particularly relevant. For Digital Twins, adoption depends on clinicians' perceptions of reliability, usability, and clinical meaning. Model outputs must be trusted, interfaces must be intuitive, and predictions must support clinical decision-making. These perceptions translate into individual-level determinants such as usability, trust in model predictions, data reliability, and perceived clinical relevance.

The ***Technology-Organization-Environment framework*** extends the analysis to the institutional level. It identifies three domains shaping adoption decisions: technological characteristics (e.g. relative advantage, complexity, compatibility), organisational conditions (e.g. leadership support, resources, innovation culture), and environmental factors (e.g. regulation, reimbursement, and external collaboration) (Tornatzky & Fleischer, 1990). Empirical studies confirm its relevance in healthcare, showing that successful adoption depends on the alignment of these interdependent domains (Greenhalgh et al., 2017; Pai & Huang, 2011).

For conceptual completeness, Diffusion of Innovation (DOI) theory explains how innovations spread across adopter categories at the system level (Rogers et al., 2019). However, as DOI focuses on macro-level diffusion rather than intra-organisational adoption processes, this thesis primarily draws on the explanatory power of TAM and TOE.

2.3.3 Factors Shaping Digital Twin Adoption in Healthcare

While theoretical frameworks such as TAM and TOE provide structured lenses for understanding technology adoption, empirical research is essential to validate these models within the complexity of real-world healthcare systems. Adoption processes in healthcare are shaped by socio-technical interdependencies that require alignment between users, technologies, and workflows (Holden & Karsh, 2010). Successful innovation depends on the coordinated interaction of technological, individual, organizational, and environmental factors within healthcare institutions (Pai & Huang, 2011).

Research on DTs confirms that adoption is a multidimensional process influenced by interactions across multiple system levels (Greenhalgh et al., 2017). Four main domains emerge from the literature.

2.3.3.1 Technological factors

Technological factors form the foundation of Digital Twin adoption. Interoperability, data security, and usability consistently emerge as critical enablers of successful implementation (Kuriakose et al., 2024). In the context of DTs, sustained adoption requires interoperable integration with hospital information systems and robust governance of multimodal data. Empirical studies show that limited data integration or insufficient cybersecurity can impede adoption even when technological maturity is high (Capacho-Alfonso et al., 2025). These findings align with the Technology Acceptance Model, as technical design directly influences perceived ease of use, user trust, and organisational readiness (Davis, 1989).

2.3.3.2 Individual factors

At the individual level, trust represents a central determinant of clinician acceptance. Adoption increases when model outputs are transparent, explainable, and clinically meaningful, thereby supporting interpretability and reliability in predictive systems. These characteristics reinforce perceived usefulness by linking DT insights directly to clinical decision-making processes (Asan et al., 2020a).

2.3.3.3 Organizational factors

Organisational factors determine whether technological potential translates into institutional practice. Empirical research identifies resource constraints, siloed information systems, and resistance to change as key barriers, while leadership commitment, digital maturity, and interdepartmental collaboration act as enablers (Brommeyer et al., 2023).

These findings align with the TOE framework, which emphasises that adoption depends on the alignment of governance structures, organisational processes, and workforce capabilities (Tornatzky & Fleischer, 1990).

2.3.3.4 Environmental factors

At the environmental level, external frameworks define the boundary conditions for adoption. Regulatory clarity regarding data protection, device classification, and reimbursement is essential to support long-term investment and scalability (Greenhalgh et al., 2017).

Fragmented regulation or misaligned economic incentives often result in pilot initiatives that fail to progress into routine use (Brommeyer et al., 2023). These dynamics underscore the importance of environmental readiness, as coherent regulation and financial alignment are prerequisites for sustainable DT adoption (Greenhalgh et al., 2017).

Taken together, these empirical insights extend the theoretical foundations of TAM and TOE by highlighting the interdependence of adoption drivers. Technological reliability strengthens clinician trust and perceived usefulness, organisational support enables workflow integration and individual acceptance, and supportive regulation reduces uncertainty and facilitates institutional commitment (Davis, 1989; Greenhalgh et al., 2017; Tornatzky & Fleischer, 1990). These relationships illustrate the systemic nature of DT adoption and show that successful scaling depends on coherence across sociotechnical domains (Holden & Karsh, 2010).

Overall, DT adoption in healthcare is shaped by the interaction of technological, individual, organisational, and regulatory factors. These interdependencies determine whether hospitals can move from isolated experimentation toward sustained institutional use.

Building on this synthesis, the following section examines the managerial capabilities and policy frameworks that influence the long-term sustainability of DT adoption.

2.4 Managerial and Policy Relevance of Digital Twins

The adoption of DTs in hospitals is a strategic and managerial decision shaped by hospitals' resources, organisational capabilities, and institutional context. This section synthesises resource-based theory, dynamic capabilities, and policy and governance perspectives to frame DT adoption as a multilayered organisational phenomenon.

2.4.1 Digital Twins as Strategic Investment Decisions

Resource-based theory starts from the premise that the firm is the primary unit of analysis and conceptualizes organizations as bundles of heterogeneous and imperfectly mobile resources. Differences in organizational outcomes arise because firms control distinct combinations of tangible and intangible resources that cannot be readily transferred or replicated across organizational boundaries. Importantly, resources are not inherently valuable. Their value depends on how they are combined, organized, and deployed within a specific organizational context (Barney et al., 2021).

From a resource-based perspective, hospitals differ in their capacity to adopt DTs because they possess heterogeneous resource endowments. DT implementation requires multiple co-specialized resources, including interoperable data infrastructures, high-quality clinical data, advanced IT systems, and organizational knowledge for integrating predictive analytics into clinical workflows. These resources must be orchestrated into an interdependent socio-technical system capable of supporting real-time data flows and simulation models (Kuriakose et al., 2024; Vallée, 2023).

A central insight of resource-based theory is that resources create value only when they are organized in ways that enable both value creation and value capture (Barney et al., 2021). For DTs, this organization depends on cross-departmental data exchange, reliable system integration, and alignment between technical and clinical components. Hospitals characterized by fragmented legacy systems, siloed data ownership, or limited analytics capabilities therefore face structural constraints that restrict feasible adoption, regardless of the general availability of DT technologies (Brommeyer et al., 2023).

At the same time, resource-based theory implies an ex-post logic of value attribution (Barney et al., 2021) The strategic value of complex and novel digital technologies such as DTs cannot be determined at the point of investment. Especially in healthcare contexts, regulatory uncertainty, long implementation cycles, and high coordination requirements make it impossible to assess resource value ex ante (Asan et al., 2020a).

Resource value becomes observable only after managerial decisions and organizational complementarities have unfolded. As a result, DT adoption cannot be explained solely by the possession of technological resources. Consequently, DT adoption should be understood as a strategic investment decision under uncertainty, in which managerial judgment determines whether, when, and how resources are committed.

While resource-based theory explains why hospitals differ in their structural capacity to pursue DT initiatives, it does not explain how such strategic choices are made when future value cannot be known ex ante (Kuriakose et al., 2024).

2.4.2 Organizational Capabilities Required for Adoption

While the resource-based theory explained what is structurally feasible, this thesis adopts Barreto's (2010) conceptualization of dynamic capabilities as the primary analytical lens for explaining how hospitals address the uncertainty associated with DT adoption.

Dynamic capabilities refer to an organization's potential to systematically solve problems under conditions of environmental change. This potential is constituted by organizational propensities to sense opportunities and threats, to make timely and market-oriented decisions, and to reconfigure the resource base.

Building on earlier efforts to extend resource-based theory to dynamic environments (Teece et al., 1997), Barreto's conceptualization deliberately avoids equating dynamic capabilities with realized actions or performance outcomes. Dynamic capabilities are a firm's potential to systematically solve problems, formed by its propensity to sense opportunities and threats, to make timely and market-oriented decisions, and to change its resource base accordingly (Barreto, 2010). Here, dynamic capabilities represent a latent organizational potential whose effects remain contingent on managerial strategic judgment, contextual conditions, and complementary organizational arrangements (Barreto, 2010; Eisenhardt & Martin, 2000). This distinction is particularly important in healthcare settings, where technological investments frequently fail to translate into sustained organizational benefits (Greenhalgh et al., 2017).

Under conditions of technological uncertainty, sensing refers to the organizational propensity to identify and interpret clinically meaningful opportunities for DT applications. Such as predicting patient deterioration, optimizing surgical planning, or modelling patient pathways. While Teece (2007) conceptualizes sensing as a core class of dynamic capabilities, Barreto (2010) emphasizes its cognitive and interpretative nature, highlighting that sensing does not imply that opportunities are necessarily recognized or acted upon.

For DTs, sensing demands are heightened because hospitals must integrate heterogeneous expertise from clinicians, IT specialists, and data scientists to assess whether simulation-based approaches may plausibly create value (Vallée, 2023). Seizing corresponds to the propensity to make timely and market-oriented decisions regarding whether and how identified opportunities should be pursued (Barreto, 2010).

Decision-making is analytically distinct from resource reconfiguration and constitutes a central mechanism through which dynamic capabilities differ from ad hoc problem solving. Whereas Teece (2007) frames seizing primarily as the commitment of resources, Barreto places greater emphasis on the quality, timing, and orientation of decisions that precede such commitments. In the context of DT adoption, seizing therefore involves governance structures capable of evaluating DT initiatives. Reallocating budgets toward data interoperability or model development, and assembling interdisciplinary teams under conditions of high upfront investment and delayed benefits (Kuriakose et al., 2024).

Transforming refers to the propensity to reconfigure the resource base by modifying organizational structures, routines, and workflows so that DTs can be integrated into everyday clinical practice. Eisenhardt and Martin (2000) conceptualize transformation as identifiable organizational processes and routines, while Barreto (2010) emphasizes that such reconfiguration becomes effective only when combined with appropriate sensing and decision-making propensities. In hospital contexts, transformation may involve redesigning clinical pathways, establishing continuous data-governance processes, restructuring collaboration between clinical and IT units, and developing new hybrid roles such as clinical data engineers (Brommeyer et al., 2023; Greenhalgh et al., 2017).

Crucially, the presence of dynamic capabilities does not imply that hospitals will necessarily appropriate value from DT initiatives. In line with Barreto's (2010) argument, dynamic capabilities should not be conflated with adoption outcomes. Value realization depends on complementary assets, governance mechanisms, and organizational arrangements that translate DT-enabled insights into institutional benefits. Accordingly, sustainable DT adoption reflects the contingent realization of organizational potential through strategic problem-solving under uncertainty, rather than the deterministic effect of technological readiness alone.

2.4.3 Policy and Governance Conditions Shaping Adoption

Beyond internal resources and capabilities, the external institutional environment critically shapes DT adoption. Policy and governance frameworks determine whether hospitals face supportive or adverse conditions when investing in advanced digital technologies (OECD, 2025). Economic incentives are particularly influential. In many health systems, payment models do not reward efficiency gains because reimbursements are fixed per case or capped by budgets (Porter & Teisberg, 2006).

As a result, reductions in complications or length of stay, outcomes that DTs may improve, do not necessarily translate into increased revenue for individual hospitals. (Greenhalgh et al., 2017). When predictive or simulation-based services lack explicit reimbursement pathways, the financial benefits accrue primarily at the system level instead of the adopting organization, weakening adoption incentives (Greenhalgh et al., 2017; Porter & Lee, 2013).

Regulatory clarity also shapes adoption. Hospitals must operate within stringent data protection regimes, certification requirements, and liability frameworks. Ambiguous or restrictive legislation increases uncertainty. It also complicates data sharing, which is essential for DT integration. Without predictable regulatory conditions, hospitals face heightened risk and reduced willingness to invest (Viceconti et al., 2024).

Interoperability and technical standards are further critical. DTs rely on consistent, high-quality data flows across multiple systems. Fragmented standards or incompatible interfaces severely limit scalability. Policy-driven interoperability initiatives therefore exert direct influence on adoption feasibility (OECD, 2025).

Ethical governance frameworks emphasize transparency, fairness, and explainability, all of which underpin trust in data-driven clinical tools. Ethical considerations are not peripheral but central to legitimacy. Mechanisms ensuring privacy, auditability, and responsible data use shape societal and professional acceptance. Without trust, even technically advanced DT systems may face resistance (Asan et al., 2020b).

For hospitals, this means that internal readiness and capabilities cannot compensate for misaligned incentives, inadequate interoperability, regulatory ambiguity, or insufficient ethical governance. DT adoption emerges from the interdependence of three theoretical layers. Resource-based theory explains the foundational constraints and opportunities embedded in hospitals' resource configurations.

Dynamic capabilities illuminate how organizations adapt these resources through sensing, seizing, and transforming activities. Policy and governance frameworks define the incentive structures, regulatory rules, and ethical boundaries that shape strategic decision-making. Together, these perspectives conceptualize DT adoption as a multilevel phenomenon in which feasibility results from the alignment of internal resources, adaptive capabilities, and external institutional conditions.

3 Methodology

3.1 Summary and Conceptual Framework

The preceding sections traced the evolution of DTs from their engineering origins to their conceptual and operational adaptation in healthcare (Section 2.1). Building on this foundation, DT applications were systematised along the healthcare value chain, distinguishing patient-facing clinical use cases for modelling and diagnostics, therapy planning, and adaptive monitoring (Section 2.2.1).

As well as system-level applications addressing clinical-administrative coordination, hospital operations, and enabling infrastructures such as data integration and interoperability (Sections 2.2.2–2.2.4).
DTs were subsequently positioned within the Disruptive Innovation framework, highlighting that current implementations reflect incremental institutional integration rather than disruptive market displacement (Section 2.3.1). Technology adoption in hospitals was then conceptualised as a multi-level process shaped by individual acceptance (TAM), organisational readiness (TOE), and environmental conditions including regulation and reimbursement (Section 2.3.2 –

2.3.3). Finally, DT adoption was reframed as a strategic and managerial challenge under uncertainty, governed by dynamic capabilities, resource configurations, and policy and governance frameworks (Section 2.4).

Against this backdrop, the present research sought to answer the central question:

What are key factors driving the adoption of Digital Twins in healthcare?

To address this question, the conceptual design of this thesis was built around an *Adoption Driver Framework* that categorizes the determinants influencing adoption across organizational levels.

3.1.1 Adoption Driver Framework

Building on this structural view, this thesis developed an **Adoption Driver Framework** that explains how and under what conditions these capabilities are realised in practice. It integrates the Technology Acceptance Model (TAM) (Davis, 1989), the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), and Dynamic Capabilities Theory (Barreto, 2010; Teece, 2007) into a unified analytical model. While adoption is conceptually defined as sustained institutional integration, the empirical analysis focuses on adoption-related conditions and mechanisms rather than direct measures of long-term implementation outcomes.

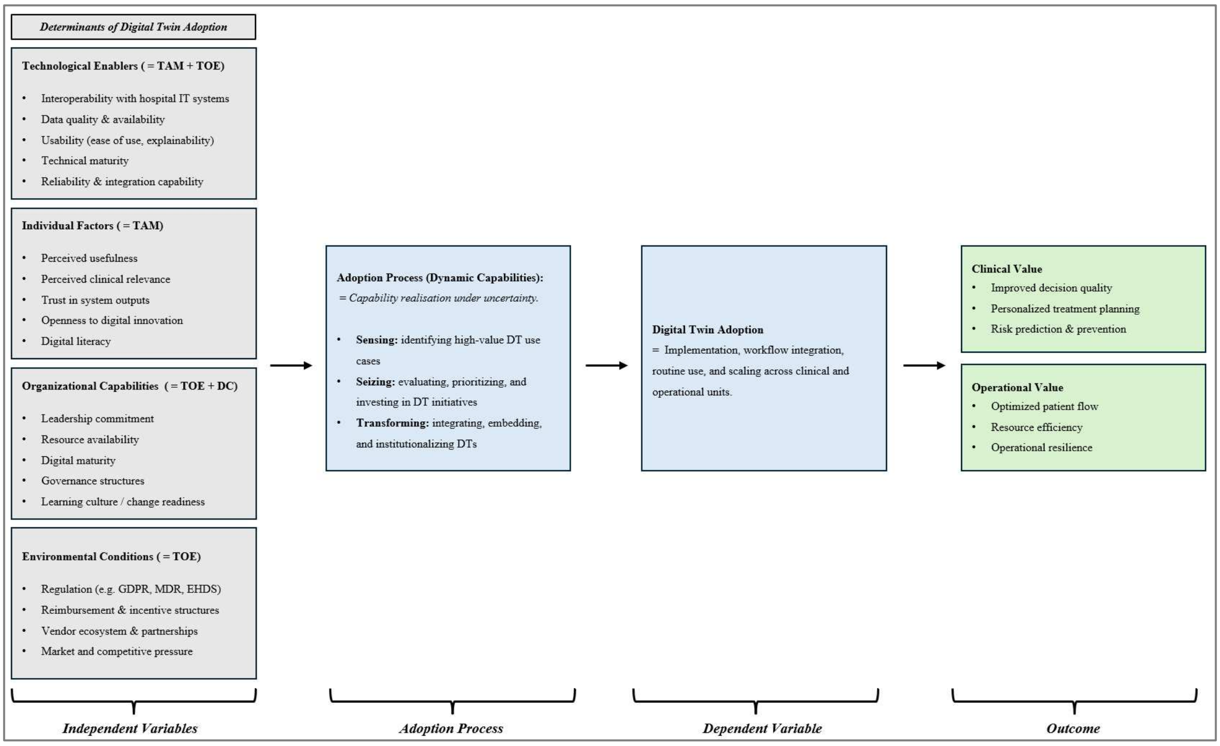

Figure 1: *Adoption Driver Framework*

Within this framework, the dependent variable is DT adoption, defined as the extent to which hospitals implement, integrate, and sustain DT solutions across clinical and operational contexts. Adoption is influenced by four interrelated groups of independent variables: technological enablers, individual factors, organizational capabilities, and environmental conditions. Together, these dimensions capture system-level characteristics, user perceptions, institutional readiness, and external boundary conditions that shape adoption feasibility.

Adoption is conceptualised not as a static acceptance decision but as the context-dependent realisation of dynamic capability propensities. Following Barreto (2010) and Teece (2007), this process unfolds through sensing high-value DT use cases, seizing them through strategic decision-making and resource mobilisation, and transforming organisational structures, workflows, and governance arrangements to enable sustainable embedding.

The interaction of technological reliability, organisational readiness, individual engagement, and supportive regulatory conditions determines whether adoption progresses beyond isolated pilots toward institutionalisation.

This forms the overarching conceptual model of this thesis:

- **Independent variables:** technological, individual, organizational, and environmental drivers.
- **Moderating and mediating variables:** factors that condition the strength and mechanisms through which adoption drivers influence Digital Twin adoption.
- **Dependent variable:** adoption of Digital Twins in healthcare organizations.
- **Outcome variables:** clinical and operational value creation.

This integrated model served as the analytical foundation for the empirical study.

3.2 Research Design

This study adopted an exploratory sequential mixed-methods design (Creswell & Plano Clark, 2018) to examine the factors that drive the adoption of DTs in healthcare. The research proceeded in three interlinked stages:

(1) a focused literature review to establish the theoretical and conceptual foundations,

(2) a series of semi-structured expert interviews with key stakeholders to generate qualitative insights, and

(3) a quantitative healthcare consumer survey to explore public perceptions of DT technology as a complementary angle.

In this thesis, *healthcare consumers* refer to individuals with prior interactions with healthcare services and thus represent an informed, patient-experienced population. This design enabled an iterative interplay between theory development and empirical investigation.

The approach was grounded in constructivist epistemology, which assumes that knowledge emerges from the interpretation of experiences rather than from objective observation (Lincoln & Guba, 1985). The qualitative component therefore served to explore the sociotechnical context surrounding DT adoption, while the survey provided a descriptive behavioural perspective.

Figure 2 illustrates the sequential structure of the research design.

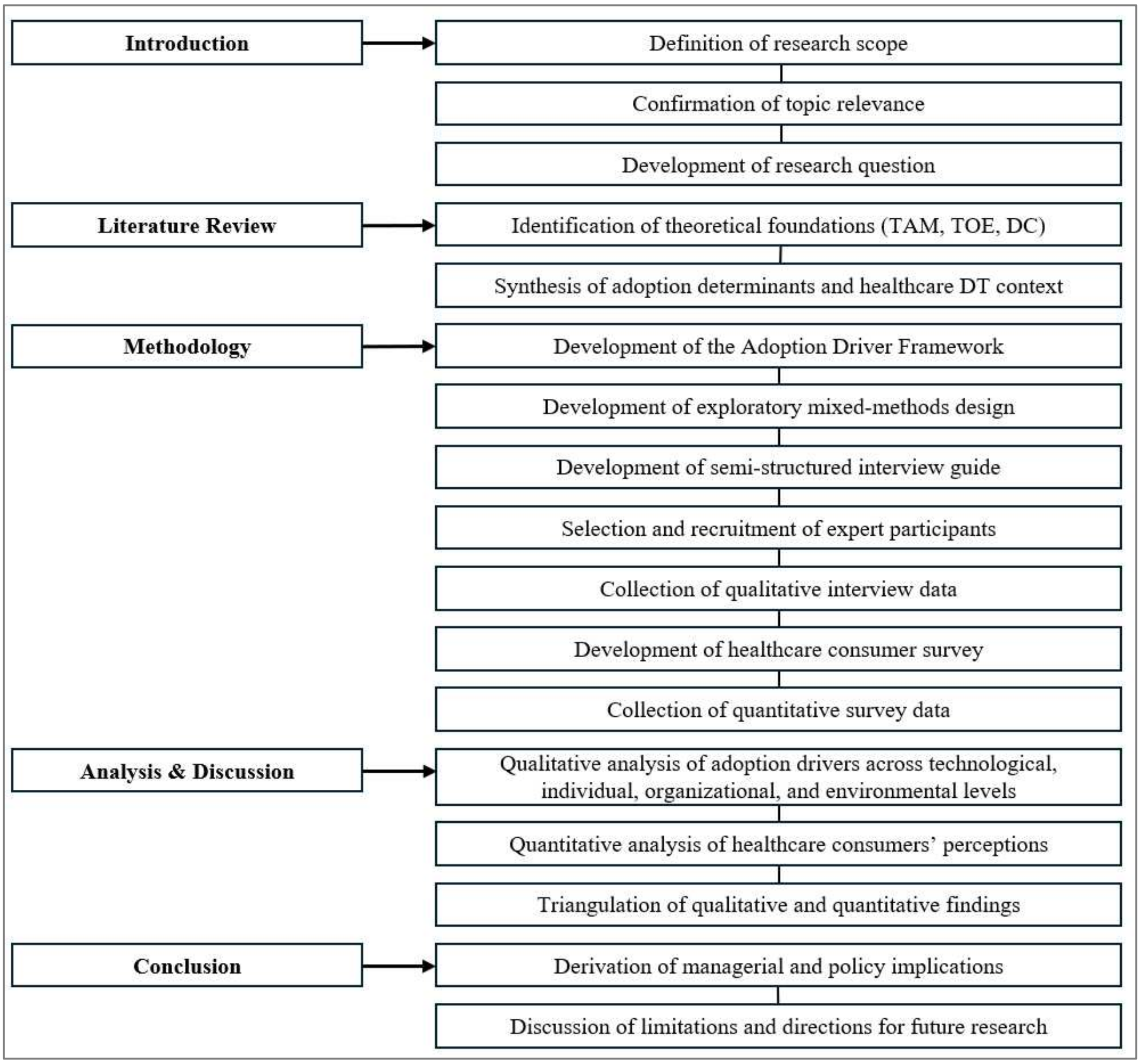

Figure 2: *Research Design*

3.3 Data Collection

3.3.1 Literature Review Strategy

The literature review synthesized academic and industry research on DT applications, technology adoption, and innovation management in healthcare. Database searches were conducted across PubMed, Scopus, and Web of Science, supplemented by Google Scholar for grey literature and recent industry reports.

Search terms included combinations of “Digital Twin,” “healthcare,” “hospital,” “adoption,” “implementation,” “technology acceptance,” and “organizational readiness.” Peer-reviewed articles used were published between 2015 and 2025, written in English, and focused on clinical or operational applications of DTs, or on relevant theoretical frameworks.

Studies outside the healthcare context were excluded unless they provided foundational theoretical insight (e.g., Grieves, 2014). The review followed a structured qualitative screening approach as outlined by Snyder (2019). Each article was assessed for conceptual contribution, methodological rigor, and relevance to the research question, ensuring that the literature review provided both a theoretical basis and practical guidance for developing the interview framework.

3.3.2 Expert Interviews (Sampling and Participants)

To explore the multidimensional drivers of DT adoption, twelve semi-structured expert interviews were conducted in November 2025 via Microsoft Teams, each lasting 30 – 45 minutes. All interviews were recorded with consent and transcribed verbatim.

The interview design was theory-driven, integrating constructs from TAM, TOE, and managerial frameworks such as the Resource-Based Theory (RBT) (Barney et al., 2021), Dynamic Capabilities (Barreto, 2010; Teece, 2007), and Value-Based Healthcare (Porter & Teisberg, 2006).

The interview guide was structured around five thematic blocks: (1) perception and value understanding, (2) organizational conditions, (3) environmental context, (4) managerial and strategic factors, and (5) trust and responsibility. A detailed version of all interview guides, tailored to each stakeholder group, is provided in Appendix A.

The sample was purposefully selected to ensure heterogeneity and cross-functional representation (Patton, 2015). Experts were drawn from five stakeholder groups: clinicians, hospital managers, consultants, MedTech professionals, and academic researchers to capture complementary insights from both the clinical and managerial spheres. Participants were identified through professional networks, LinkedIn outreach, and snowball sampling.

The sample size was determined by data saturation, which serves as a key criterion in qualitative research. During the coding process, no new themes emerged beyond the tenth interview, and interviews eleven and twelve confirmed thematic redundancy (Guest et al., 2006). Therefore, data collection was concluded after twelve interviews.

This aligned with methodology studied indicating that saturation in theory-driven expert studies is typically reached within approximately 6–12 interviews (Hennink & Kaiser, 2022). Summaries of all interviews, including key themes and contextual information, are included in Appendix B.

Table 1 provides an overview of the expert sample (anonymized for confidentiality).

Code	Expertgroup	Current position and expertise
E01	Consultant	Senior Consultant at Roland Berger specialising in digital health transformation, with strong experience in data-driven innovation, technology adoption, and strategic implementation in healthcare settings.
E02	Consultant	Senior Manager for Digital Health Transformation at Accenture with extensive experience leading innovation and data-driven programmes across clinical, operational, and digital domains.
E03	Consultant	Senior Partner for AI & Data at Deloitte Canada with deep expertise in healthcare analytics, data strategy, and AI-enabled decision support across complex health systems.
E04	Consultant	Senior Manager at Roland Berger's Digital Health team, specialising in hospital digitalisation across Germany and leveraging a strong IT background to drive data-enabled transformation and modernisation of clinical and operational infrastructures.
E05	Physician	Orthopaedic and trauma surgery resident with clinical experience across leading German hospital systems and additional expertise as team physician for national youth teams.
E06	Hospital Management	Chief Information Security Officer and head of the digital transformation office at University Hospital Mainz, effectively operating in a Chief Digital Officer capacity by leading hospital-wide digital strategy and technology modernisation.
E07	Academic Researcher	Professor of Digital Health at Catolica Lisbon and former Chair of the EU eHealth Network, responsible for coordinating European Member States on health data and interoperability policy while simultaneously holding senior leadership roles in Portugal.
E08	MedTech	Chief of Staff at a MedTech startup, supporting the CEO and executive team by coordinating strategic initiatives, driving organisational alignment, and overseeing key cross-functional projects within a rapidly scaling health-technology environment.

E09	Physician	Chief Physician of Cardiology at the University Medical Center Mainz, with eight years of departmental leadership overseeing interventional cardiology, electrophysiology, and heart-failure care.
E10	Consultant	Senior Consultant for Digital Health at Roland Berger with a background in health economics and experience advising healthcare organisations on digital transformation, strategic innovation, and data-driven operating models.
E11	MedTech	Head of Business Development at one of the world's leading MedTech companies, overseeing strategic growth initiatives, partnerships, and market development within a global innovation-driven environment.
E12	Academic Researcher	Professor of Medical Informatics at HTWG Konstanz and founder of Wache eHealth Consulting, serving as a leading voice in Germany's digital health community through his widely recognized podcast on health and medical informatics

Table 1: *Overview of expert interview sample (anonymized)*

3.3.3 Healthcare Consumer Insights Survey

To complement the expert interviews and extend the analysis to the individual level, a quantitative healthcare consumer survey was conducted using Qualtrics. This component captured individual attitudes toward Digital-Twin-supported physicians, including trust, perceived usefulness, openness to digital health technologies, risk perception, and willingness to share health data.

Data were collected online and distributed through digital channels and personal networks. After removing pretest cases, incomplete questionnaires, responses failing the attention check (n = 11), and submissions with implausibly short completion times below 90 seconds (n = 6), the final cleaned dataset comprised 244 valid responses.

The questionnaire contained 36 items, including multiple-choice questions and several five-point Likert-type scales. It covered:

- respondents' healthcare experiences (E.g., chronic conditions, prior long-term treatment, wearable use),
- perceptions of patient-level and hospital-level DTs, openness towards digital health,
- major concerns (E.g., privacy, biased recommendations, loss of human interaction),
- satisfaction with the healthcare system,
- and willingness to share personal health data.

The full questionnaire is presented in Appendix D.

3.4 Data Analysis

The qualitative data from expert interviews were analysed using Mayring's (2015) method of qualitative content analysis. In line with this approach, a formal coding guideline was developed prior to full-scale coding. It specified category definitions, anchor examples, coding rules, and exclusion criteria for all deductively derived dimensions. The initial category system comprised six higher-order determinants of DT adoption (technological, organisational, environmental, individual, managerial/strategic, and value-related), each operationalised through theoretically grounded subcategories.

Coding was conducted at the level of meaning-carrying statements, while retaining the interview context to avoid decontextualization. Following a pilot coding phase, category definitions and boundaries were refined before the full dataset was coded.

In addition to qualitative interpretation, frequency counts, expert coverage per category, and co-occurrence patterns across categories were systematically analysed to identify dominant adoption mechanisms and cross-cutting meta-patterns. These analytical steps form the empirical basis of the findings presented in Section 4.2. The full coding guideline and supporting tables are provided in Appendix C.

Survey data were analysed quantitatively using SPSS. After data cleaning, descriptive statistics were computed, followed by inferential testing using ANOVA, ANCOVA, chi-square tests, logistic regression, and linear regression. The selection was based on variable type and conceptual purpose.

Several variables were measured using five-point Likert-type scales but were treated as approximately continuous, consistent with evidence on the robustness of parametric procedures for large samples (Olsson, 2022). A two-step modelling strategy was applied, estimating fully adjusted models with demographic covariates followed by reduced models to assess the robustness of focal effects.

3.5 Research Quality

Methodological rigor was a central concern throughout the research process. The qualitative component followed the trustworthiness criteria proposed by (Lincoln & Guba, 1985): credibility, transferability, dependability, and confirmability.

- Credibility was enhanced through triangulation of data sources (literature, expert interviews, survey) and through the inclusion of diverse professional perspectives. It was further supported by achieving data saturation by the twelfth interview, ensuring that additional interviews would not have yielded substantively new insights.

- Transferability was supported by detailed contextual description, enabling readers to assess the applicability of findings to other settings.
- Dependability was ensured by maintaining a transparent audit trail documenting all stages of data collection and analysis.
- Confirmability was addressed through reflexivity and by basing interpretations strictly on evidence derived from the data.

Ethical standards were upheld throughout. Participants provided informed consent, anonymity was ensured through pseudonymisation, and all recordings and transcripts were stored securely and used exclusively for research purposes.

4 Findings

4.1 Findings from Literature Review

This section synthesises the key findings of the literature review presented in Chapter 2. The literature review showed that the DT concept evolved from aerospace engineering and product lifecycle management toward Medical Digital Twins. In healthcare, MDTs combine mechanistic modelling with AI-based learning to create dynamic, patient-specific representations.

Building on Porter and Teisberg's Value-Based Healthcare framework, DT applications in hospitals were classified into three interlinked layers of value creation. Clinical applications directly improved patient outcomes, while clinical-administrative applications optimised care delivery and operations. Administrative-support applications targeted structural cost drivers and operational continuity. Across all application layers, interoperability, robust data infrastructures, and cybersecurity emerged as enabling capabilities without which DTs remain fragmented technical artefacts.

Regarding adoption, the literature positioned DTs within Disruptive Innovation Theory. However, empirical evidence showed that current applications remained largely sustaining in nature and concentrated in highly resourced institutions.

Adoption was conceptualised through the TAM and the TOE framework as a multilevel socio-technical process. At the technological and individual levels, adoption was shaped by system reliability, usability, perceived usefulness, and trust. At the organisational and environmental levels, leadership, digital maturity, cross-departmental collaboration, regulation, and reimbursement conditions played a decisive role.

From a resource-based and dynamic capabilities perspective, DTs were framed as strategic investment contexts. In these contexts, hospitals mobilise latent organisational capabilities to sense opportunities and make targeted resource-allocation decisions. Over time, adoption requires the reconfiguration of structures and routines. Policy, governance, and ethical frameworks define the external boundary conditions within which such transformation processes can unfold sustainably.

4.2 Findings from the Expert Interviews

The expert interviews revealed a multifaceted and uneven landscape of DT adoption in healthcare. Across all interviews, adoption emerged as the outcome of interdependent technological, organisational, environmental, individual, and strategic conditions rather than isolated drivers.

Building on the systematic qualitative coding procedure outlined in Section 3.4 and documented in Appendix C, the following sections synthesise the empirically derived findings from the expert interviews.

4.2.1 Technological Determinants

Technological determinants represented the most frequently referenced category (107 coded segments) and formed the structural foundation of DT readiness. Data quality and interoperability (A3) as well as technical maturity (A4) were consistently described as prerequisite conditions for any meaningful DT application.

Ten experts characterised hospital data environments as fragmented, siloed, or poorly standardised, with legacy systems producing inconsistent or unstructured data. As one expert stated, "*A digital twin is only as good as the data it receives*" (E03). Limited semantic interoperability and the continued reliance on PDF-based documentation hinder real-time data flows and undermine dynamic model updates.

Concerns regarding technical maturity were raised by eleven experts. They emphasised the need for stable data pipelines, robust PACS/RIS integration, and reliable system performance. Such conditions were typically confined to highly digitalised specialties such as radiology and neurosurgery, described as "islands of excellence" rather than system-wide capability.

Infrastructure limitations (A5), including unreliable Wi-Fi, outdated hardware, and non-scalable on-premises systems, further constrained implementation efforts. Clinicians prioritised low-click, workflow-integrated solutions, whereas researchers and vendors highlighted the inherently iterative and resource-intensive nature of DT development. This maturity gap helps explain why ease of use (A2) repeatedly emerged as a relevant adoption determinant: tools that increased cognitive load or required additional screens were consistently rejected in time-critical clinical settings.

Across stakeholder groups, clinicians primarily emphasised clinical risk and system reliability, while consultants and researchers focused more strongly on scalability and modelling constraints. Overall, technological determinants constituted the strongest meta-pattern and shaped what experts repeatedly referred to as the "baseline feasibility" of DT adoption.

4.2.2 Organisational Determinants

Organisational determinants (56 coded segments) explained why promising DT technologies often failed to translate into routine clinical practice. Workflow integration (B3) emerged as a central issue: nine experts stressed that DT tools must fit seamlessly into established routines, particularly in surgery, radiology, and emergency care. As one clinician stated, "*If it costs me more than a few clicks or a few minutes, it will not be used*" (E05).

Persistent resource constraints further reinforced these challenges. Experts referred to limited project management capacity, insufficient IT support, and inadequate documentation assistance. While hospitals acknowledged DTs' strategic relevance, limited operational bandwidth created a recurring adoption paradox.

Leadership support (B4) and governance structures (B5) were also identified as decisive determinants. Eight experts noted that without clear board-level sponsorship, DT projects rarely progressed beyond pilot phases. Interviewees described fragmented coordination between clinical, operational, and IT units, unclear responsibilities, and slow decision-making processes. As a result, DT initiatives frequently emerged as isolated local efforts without institutional anchoring. Across stakeholder groups, clinicians primarily framed organisational barriers in terms of workflow burden, whereas managers and consultants emphasised governance and coordination deficits.

Organisational determinants therefore acted as structural mediators: even where technological potential existed, adoption stalled in the absence of workflow fit, organisational capacity, and effective governance.

4.2.3 Environmental Determinants

Environmental determinants (76 coded segments) exerted a systemic influence on DT adoption trajectories, with regulation (C1) and market incentives (C2) dominating expert discussions. Seven experts identified the Medical Device Regulation (MDR) as a major constraint due to long approval cycles, extensive documentation requirements, and uncertain implementation pathways. Interpretations of the GDPR varied across interviews: a minority viewed consent-driven architectures as potential enablers, while most perceived compliance obligations as slowing innovation. As one expert summarised, "*Regulation is not the enemy, but the way hospitals interpret it often is*" (E12).

Market dynamics created heterogeneous adoption incentives across clinical domains. High-volume and high-revenue specialties, particularly oncology and radiology, exhibited stronger drivers for DT adoption, whereas general wards and resource-constrained public hospitals faced weaker pressures. This divergence contributed to uneven adoption patterns across specialties.

Vendor ecosystems (C3) characterised by proprietary interfaces, vendor lock-in effects, and inconsistent standards, further limited interoperability and cross-institutional learning. Funding schemes (C4) were acknowledged as supportive but insufficient for sustained capability building, as short-term grants rarely address deeper structural or organisational deficits.

Policy and MedTech experts discussed regulatory constraints far more extensively than clinicians, reflecting differing proximities to compliance and approval processes. Overall, environmental determinants functioned as external structural forces whose influence varied by specialty, institutional readiness, and regulatory interpretation.

4.2.4 Individual Determinants

Individual determinants (44 coded segments) shaped behavioural readiness for DT adoption at the point of care. Trust (D1) emerged as the most salient individual-level mechanism. Clinicians consistently rejected DT tools perceived as opaque or unpredictable. As one cardiologist remarked, "*If it feels like a black box, I'm out"* (E05).

Trust was shaped by perceived system reliability and alignment with clinical judgement. Openness to innovation (D3) varied across generations and clinical domains. Younger clinicians and digitally mature specialties expressed greater enthusiasm, whereas older staff and roles characterised by high workload were more likely to exhibit scepticism or digital fatigue. These differences help explain variation in transformation readiness within the same institution.

Digital skills (D4) were unevenly distributed across professional groups. Experts noted that IT staff often lacked detailed understanding of clinical processes, while clinicians typically lacked modelling expertise or data literacy. This gap was particularly relevant for DTs, which require sustained interdisciplinary collaboration.

Across stakeholder groups, clinicians foregrounded trust and usability concerns, while consultants and researchers focused more strongly on competence gaps and cognitive barriers. Individual determinants therefore acted as behavioural filters shaping acceptance, speed of adoption, and the sustainability of DT use in clinical settings.

4.2.5 Managerial and Strategic Determinants

Managerial determinants (44 coded segments) linked organisational conditions with long-term strategic direction. Across interviews, experts emphasised that DTs were not perceived as isolated technologies but as strategic transformation initiatives. Their successful implementation required dynamic capabilities (E1), structured resource orchestration (E2), and alignment with institutional priorities such as precision medicine and operational efficiency (E3).

Leadership commitment and governance structures (E4) were repeatedly identified as decisive factors. As one hospital leader stated, "*Without leadership support, nothing moves*" (E09). Experts highlighted that sustained investment in interdisciplinary teams, data engineering capacity, and long-term capability building was necessary to advance DT initiatives beyond pilot stages.

Clinicians tended to interpret leadership effects primarily in terms of operational support, whereas executives and consultants associated them with strategic alignment and long-term capability development. Managerial determinants therefore functioned as strategic accelerators: when present, they compensated for structural deficits. When absent, they reinforced organisational stagnation.

4.2.6 Value Creation Potential

Value-related determinants (72 coded segments) represented the core justification logic for DT adoption. Experts identified clinical value (F1), operational value (F2), and commercial or competitive value (F3) as the primary motivators underlying adoption decisions.

Clinicians emphasised improved diagnostic accuracy, enhanced surgical planning, reduced complication rates, and more personalised care pathways. Consultants and managers highlighted operational efficiencies, including throughput gains and reduced error rates. In MedTech contexts and high-volume centres, commercial value propositions such as differentiation, innovation branding, and long-term revenue logic were particularly prominent.

Despite these perceived benefits, experts agreed that the realisation of value from DTs depended heavily on structural readiness. Early-stage implementations often generated localised benefits but rarely scaled without robust data quality, effective workflow integration, and appropriate governance structures.

4.2.7 Cross-Cutting Synthesis

Across the expert interviews, several overarching mechanisms became apparent. Foundational data readiness emerged as the strongest determinant of DT maturity. Without structured, interoperable, and timely data, neither technical functionality nor clinical value could be realised. Workflow fit and trust acted as behavioural gatekeepers, shaping whether DT tools were accepted and used at the point of care.

Leadership, governance, and organisational alignment determined whether DT initiatives progressed beyond pilot projects toward institutionalised capabilities. In parallel, clinical, operational, and commercial value logics influenced adoption incentives and investment priorities across medical specialties.

Taken together, these findings indicate that DT adoption is driven by interdependent, multi-level mechanisms rather than isolated factors.

4.3 Findings from the Health Consumer Insights Survey

The healthcare consumer survey served as the quantitative component of the mixed-methods research design and was developed to empirically test the individual-level mechanisms that emerged from the expert interviews.

The qualitative phase identified trust, perceived usefulness, privacy expectations, sensitivity to negative information, and digital readiness as mechanisms and conditions shaping DT adoption. These themes therefore required systematic examination at the patient level.

To enable empirical testing, the qualitative insights were translated into eight hypotheses grounded in established technology-acceptance and risk-perception frameworks, focusing on attitudinal and experiential antecedents of behavioural intentions. The analyses did not aim to predict hospital-level adoption but to contextualise qualitative insights with empirical evidence from the consumer perspective.

Each hypothesis was tested using an appropriate statistical method (ANOVA, ANCOVA, chi-square tests, logistic regression, or multiple regression), depending on variable scale. All models were tested for assumption validity. Levene's Test indicated no violation of homogeneity of variances (all $p > .05$), and Breusch–Pagan tests showed no evidence of heteroskedasticity (all $p > .05$). These diagnostics confirm that the ANOVA and regression results reported below can be interpreted without adjustment.

A total of n=244 valid responses were retained after data cleaning, which consisted of removing pretest cases, failed attention checks, and responses below a 90-second completion threshold. The sample was demographically diverse, with most respondents aged 25 – 44, a balanced gender distribution, and representation from over twenty countries, primarily the United States and Europe. Most participants worked outside healthcare, while smaller groups reported clinical or technology backgrounds. More than one third reported living with a chronic condition (36.9%). Overall awareness of DTs was relatively high, with moderate perceived usefulness and high openness toward digital health technologies. Descriptive statistics are reported in Appendix E.

Initial descriptive analyses provided a first overview of participants' attitudes DT technology. Perceived usefulness was evaluated positively at both the hospital level and the patient level. The near-identical mean values and comparable dispersion indicate a consistent perception of usefulness across levels, with only minor negative skewness.

	N	Mean	Std. Deviation
Perceived usefulness (hospital level)	244	3.84	0.713
Perceived usefulness (patient level)	244	3.80	0.780

Table 2: *Descriptive statistics of perceived usefulness*

Openness toward DT technology showed a similar pattern, indicating that respondents were generally receptive rather than divided in their views.

	N	Mean	Std. Deviation
Openess towards DT-technology	244	3.69	0.861

Table 3: *Descriptive statistics of openness towards Digital Twin*

Willingness to share personal health data was somewhat lower but still moderately positive.

	N	Mean	Std. Deviation
Willingness to share data	244	3.68	0.810

Table 4: *Descriptive statistics of willingness to share personal health data*

These descriptive patterns provided important context for the subsequent inferential analyses, as they reflect a sample that is digitally informed and comparatively experienced, characteristics that are likely to influence attitudes toward complex technologies such as Digital Twins.

Building on this descriptive profile, the following section examines eight analytical hypotheses.

4.3.1 Effect of Trust Orientation on Willingness to Share Personal Health Data

Hypothesis 1 stated that individuals with stronger trust orientation toward DT-supported medical decisions exhibit a higher willingness to share personal health data. Trust emerged as a central mechanism in the qualitative phase, suggesting a potential link between trust and disclosure intentions.

ANOVA was applied to compare mean differences across trust-orientation groups, with demographic variables and concern categories included as controls. Non-contributing predictors were excluded to obtain a parsimonious model. The final model showed that trust orientation was significantly associated with willingness to share data ($p = .022$). However, age ($p = .001$) and industry background ($p = .018$) had stronger explanatory power, indicating that data-sharing behaviour is influenced more by broader sociodemographic dispositions than by trust orientation alone.

Overall, the effect of trust was statistically significant but small in magnitude, indicating limited practical relevance compared to sociodemographic factors. Nevertheless, given the statistically significant main effect ($p = .022$), the null hypothesis was rejected.

Dependent Variable: Willingness to share data

Source	df	F	p	Partial Eta Squared
Trust	2	3.865	.022	.034
Age	4	5.152	.001	.085
Industry	2	4.119	.018	.036

Table 5: *Between-subjects ANOVA results for willingness to share data*

4.3.2 Effect of Wearable Use on Openness Towards Digital Twin Technologies

Hypothesis 2 stated that individuals with prior digital engagement, measured through wearable use, exhibit higher openness toward DT technologies. Qualitative insights suggested that familiarity with digital health tools reduces psychological barriers to advanced innovations.

ANOVA was applied to compare openness across wearable-use groups. Wearable use showed a strong and highly significant effect ($p < .001$), while non-contributing demographic variables were removed during model refinement.

Overall, the effect was not only statistically significant but also practically meaningful, indicating that digital literacy acquired through everyday technology use has a substantive impact on openness toward emerging DT technologies. Accordingly, the null hypothesis was rejected.

Dependent Variable: Openess towards DT-technology

Source	df	Mean Square	F	p	Partial Eta Squared
Wearables	2	5.909	10.642	.000	.084
Age	4	3.930	7.078	.000	.109
Income	2	3.994	7.193	.001	.059

Table 6: *Between-subjects ANOVA results for openness toward Digital Twin technology*

4.3.3 Effect of Chronic Health Conditions on Perceived Usefulness

Hypothesis 3 stated that individuals with chronic health conditions perceive patient-level DTs as more useful than individuals without chronic conditions.
The qualitative phase emphasised that chronic patients may particularly benefit from personalised simulation and continuous monitoring.

ANOVA was applied because perceived usefulness was treated as an interval-level construct, and differences across chronic-condition categories were of interest. Interaction effects were intentionally excluded to retain interpretive clarity.

After estimating a full model, non-significant variables were removed to sharpen the analysis. The refined model showed that chronic condition status significantly predicted perceived usefulness at the patient level ($p = .001$). Respondents with chronic conditions consistently evaluated DT applications more positively than those without such experience.

Overall, the effect was moderate in magnitude, underscoring that personal health status is a meaningful driver of value attribution for patient-level DT applications. Accordingly, the null hypothesis was rejected.

Dependent Variable: Perceived usefulness (patient level)

Source	df	F	p	Partial Eta Squared
Chronic Condition	1	10.518	.001	.045
Age	4	2.267	.063	.039
Income	2	3.613	.029	.031
Industry	2	2.792	.063	.024

Table 7: *Between-subjects ANOVA results for perceived usefulness (patient level)*

4.3.4 Effect of Openness on Trust Reduction after Negative DT Events

Hypothesis 4 stated that individuals with higher openness toward digital health technologies experience smaller reductions in trust following negative DT–related events. ANOVA was chosen because the dependent variable approximated interval-level measurement and group comparisons were required. Interaction terms were not included to preserve a parsimonious modelling strategy.

An ANOVA revealed openness as the only meaningful predictor of trust reduction ($p < .001$), with non-significant demographic variables removed during refinement. Higher openness was associated with substantially smaller declines in trust. No demographic variable influenced this pattern meaningfully.

Overall, the effect was substantial, indicating that attitudinal readiness toward digital health meaningfully buffers individuals against negative technology events. Accordingly, the null hypothesis was rejected.

Dependent Variable: Trust reduction after neg. report

Source	df	F	p	Partial Eta Squared
Openess to Innovation	1	14.352	.000	.059
Age	4	.658	.622	.011
Gender	1	.050	.824	.000
Income	2	2.668	.072	.023
Industry	2	3.546	.030	.030

Table 8: *ANOVA results for trust reduction following negative information*

4.3.5 Trust Orientation and the Desire for Data Control Rights

Hypothesis 5 stated that individuals with lower trust in DT-supported physicians express stronger expectations for data control rights, such as access and deletion rights. The underlying assumption was that scepticism toward algorithmically supported clinical decision-making would translate into heightened sensitivity to issues of data ownership and autonomy. A chi-square test was applied because both trust orientation and desired control rights were categorical variables. As chi-square does not accommodate interaction effects, none were modelled.

The analysis yielded no significant relationship between trust orientation and preferences for access or deletion rights ($p = .143$). Expectations for data sovereignty were uniformly high across all trust groups, indicating that preferences for controlling personal health data are not meaningfully shaped by attitudes toward DT-supported versus traditional physicians.

Chi-Square Tests

	x2	df	p
Pearson Chi-Square	3.885	2	.143
N	218		

Table 9: *Chi-square test results*

Overall, the absence of a statistically significant association indicates that the null hypothesis was not rejected, suggesting that expectations for data autonomy function as a generalised normative standard rather than a technology-specific attitude.

4.3.6 Perceived Usefulness and Willingness to Pay for DT-Enabled Services

Hypothesis 6 stated that higher perceived usefulness of DTs is positively associated with a willingness to pay for DT-enabled healthcare services. Logistic regression was applied because the dependent variable was dichotomised to model the likelihood of affirmative payment intentions. Interaction terms were omitted to ensure model stability and interpretability given the modest sample size.

An initial logistic regression including perceived usefulness at both levels and all demographic variables showed that several predictors did not meaningfully contribute and were removed in successive refinement steps. The final model retained hospital-level perceived usefulness ($p = .018$) and income ($p = .002$) as significant predictors, with model fit remaining modest but meaningful ($R^2 \approx .13$). The stepwise approach was applied exploratorily to identify robust patterns rather than to estimate stable causal models.

Overall, the results indicated that perceived usefulness influences willingness to pay, albeit with limited explanatory power. Given the statistically significant effect of hospital-level perceived usefulness, the null hypothesis was rejected.

Variables in the Equation									
								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	p	Exp(B)	Lower	Upper
Step 1	Perceived usefulness (hospital level)	-.535	.249	4.618	1	.032	.586	.360	.954
	Perceived usefulness (patient level)	.209	.229	.831	1	.362	1.232	.786	1.931
	Gender(1)	.090	.308	.085	1	.771	1.094	.598	2.003
	Income class			9.283	2	.010			
	Income class(1)	-1.320	.721	3.347	1	.067	.267	.065	1.099
	Income class(2)	-.947	.327	8.375	1	.004	.388	.204	.737
	Industry			2.269	2	.322			
	Industry(1)	.452	.548	.682	1	.409	1.572	.537	4.597
	Industry(2)	.745	.525	2.016	1	.156	2.107	.753	5.895
	Constant	.710	1.119	.403	1	.526	2.034		
Step 4	Perceived usefulness (hospital level)	-.500	.212	5.580	1	.018	.607	.401	.918
	Income class			10.323	2	.006			
	Income class(1)	-1.299	.702	3.429	1	.064	.273	.069	1.079
	Income class(2)	-.959	.314	9.327	1	.002	.383	.207	.709
	Constant	1.991	.798	6.224	1	.013	7.325		

Table 10: *Stepwise logistic regression models predicting willingness to pay*

4.3.7 Risk Perception and Willingness to Share Health Data

Hypothesis 7 stated that higher perceived risks associated with DT technologies reduce individuals' willingness to share personal health data. ANOVA was selected because the dependent variable was treated as interval-level and group differences across risk categories were evaluated. Interaction effects were not modelled to maintain analytical parsimony.

Only concerns about wrong or biased recommendations significantly reduced willingness to share data ($p = .030$). Privacy concerns, fairness concerns, and general discomfort with data use did not reach significance.

Demographic influences were also present: willingness to share data decreased among respondents aged 35–54 and among individuals outside the healthcare sector. The refined model demonstrated moderate explanatory power ($R^2 \approx .186$).

Overall, the effect was moderate, indicating that algorithmic reliability rather than privacy concerns constitutes the key psychological barrier to data disclosure in DT contexts. Accordingly, the null hypothesis was partially supported and therefore rejected in its general form.

Dependent Variable: Willingness to share data						
Source	Type III Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Corrected Model	27.593[a]	15	1.840	3.221	.000	.186
Trust	2.765	2	1.382	2.421	.091	.022
Concerns	.879	4	.220	.385	.820	.007
Age	10.056	4	2.514	4.402	.002	.077
Gender	.009	1	.009	.016	.899	.000
Income	.663	2	.331	.580	.561	.005
Industry	4.461	2	2.231	3.906	.022	.036

a. R Squared = ,186 (Adjusted R Squared = ,128)

Table 11: *ANOVA results for willingness to share data*

4.3.8 Effect of Healthcare System Satisfaction on Perceived Usefulness

Hypothesis 8 stated that lower satisfaction with the national healthcare system is associated with higher perceived usefulness of hospital-level DTs. Multiple regression was employed because the dependent variable was continuous, and multiple predictors were assessed simultaneously. Interaction effects were excluded to retain interpretive clarity and avoid overfitting. Lower system satisfaction was significantly associated with higher usefulness perceptions (p = .005). Industry background (p = .035) and income (p = .020) also influenced evaluations. The final model demonstrated solid explanatory power (adjusted $R^2 = .205$).

Model	Unstandardized Coefficients		p
	B	Std. Error	
Healthcare system rating	-.191	.067	**.005**
Gender=Male	.162	.085	.058
Industry=Technology	-.123	.141	.383
Industry=Other	-.287	.135	**.035**
Income=Low income	.428	.183	**.020**
Income=Medium income	.171	.098	.083
Age=55 or older	-.408	.287	.157
Age=45-54 years old	-.530	.227	**.020**
Age=35-44 years old	-.326	.190	.087
Age=25-34 years old	-.126	.183	.491

a. Dependent Variable: Perceived usefulness (hospital level)

Table 12: *Multiple linear regression coefficients*

Overall, the effect was meaningful, indicating that dissatisfaction with existing healthcare structures strengthens the perceived value of DT-based organisational innovations. Accordingly, the null hypothesis was rejected.

5 Discussion

This discussion advances the central argument that DT adoption in healthcare is primarily constrained by the alignment of technological and organisational capabilities rather than by individual acceptance or regulatory incentives. Individual attitudes such as trust and openness shape adoption trajectories but function mainly as mediating mechanisms rather than as primary drivers.

To structure the discussion, adoption drivers are differentiated by their functional role in the adoption process. ***Primary drivers*** define the conditions under which adoption becomes feasible. ***Secondary drivers*** influence the speed, scope, and distribution of adoption once these conditions are met. ***Mediating and moderating drivers*** shape how strongly adoption mechanisms translate into behaviour but do not independently trigger adoption. The distinction between primary, secondary, and mediating drivers reflects their relative functional role within the observed adoption processes rather than a strict causal hierarchy. This structure enables a multi-method triangulation that integrates convergences and divergences across all data sources to refine the understanding of DT adoption in practice.

5.1 Primary Drivers: Capability Alignment as the Core Mechanism

Prior literature identifies data interoperability, system integration, and organisational readiness as prerequisites for DT implementation (Brommeyer et al., 2023; Greenhalgh et al., 2017; Kuriakose et al., 2024). The findings of this thesis strongly support this view. Across both expert interviews and survey-based indicators of digital maturity, adoption failures were primarily driven by insufficient infrastructural and organisational capacity rather than by a lack of user acceptance.

Across all data sources, DT adoption consistently emerges as a capability-constrained process rather than a function of individual willingness. This convergence directly supports the Adoption Driver Framework, which conceptualises adoption as the alignment of technological readiness, organisational integration, and context-dependent usefulness rather than as a standalone acceptance decision.

5.1.1 Technological readiness as a non-negotiable foundation

The literature characterises DTs as data-dependent systems whose reliability relies on interoperability, data quality, and secure real-time synchronisation (Han et al., 2023; Kuriakose et al., 2024). The expert interviews support this view and indicate that these enabling conditions form the structural baseline for any meaningful application.

Technological readiness therefore did not simply enable adoption but defined its feasibility boundary. Where interoperable data infrastructures and reliable real-time integration were absent, adoption failed regardless of clinician attitudes or patient openness.

The survey indirectly supports these findings. High perceived usefulness and openness were observed mainly among respondents embedded in digitally mature environments, indicating convergence across all three data sources. In the absence of robust data flows and mature infrastructures, DT adoption does not fail because clinicians or patients resist it; it fails because the system cannot sustain it. This pattern aligns with the Dynamic Capabilities perspective, in which weak sensing foundations constrain subsequent seizing and transformation processes.

5.1.2 Organizational integration and leadership as adoption accelerators

While technological readiness makes adoption possible, organisational integration converts potential into practice. The expert interviews show strong agreement that workflow fit, governance consistency, and leadership sponsorship determine whether DTs progress beyond isolated prototypes. These findings align with the TOE framework, which emphasises organisational readiness as a key adoption condition (Tornatzky & Fleischer, 1990).

Survey results further indicate that organisational conditions shape individual responses indirectly. Age and professional background moderated openness and willingness to share data, suggesting that organisational digital maturity influences how users interpret and engage with emerging technologies. Organisational capabilities therefore represent the most actionable levers for accelerating DT adoption.

5.1.3 Perceived usefulness across capability domains

Perceived usefulness emerged as the only factor consistently linking technological enablers, organisational readiness, and individual attitudes. Prior TAM research positions usefulness as central to acceptance mechanisms (Davis, 1989), while expert interviews showed that clinicians legitimised DT adoption through improved diagnostic precision, risk stratification, and workflow optimisation.

The survey quantitatively supports these patterns: respondents with chronic conditions reported significantly higher usefulness evaluations, and dissatisfaction with the healthcare system was associated with higher perceived usefulness at the hospital level. Perceived usefulness therefore does not represent a fixed individual attitude, but a contextual evaluation shaped by clinical need and institutional performance.

5.2 Secondary Drivers: Contextual Enablers and Structural Constraints

Secondary drivers do not determine whether adoption occurs but influence its speed, depth, and scope under different institutional and regulatory conditions.

While prior literature often frames regulation and data protection as primary barriers to digital health adoption, the empirical findings suggest a more differentiated role (Greenhalgh et al., 2017). Experts emphasised regulatory uncertainty as a strategic constraint, whereas survey respondents did not associate privacy concerns with a reduced willingness to engage with DTs. This indicates that regulatory barriers primarily shape institutional decision-making rather than individual acceptance.

5.2.1 Market incentives and specialty-specific dynamics

The interviews indicate that DT adoption trajectories vary substantially across clinical specialties. High-volume fields with established digital infrastructures, such as oncology and radiology, show higher uptake due to clearer value pathways. Prior literature supports this pattern, suggesting that technological adjacency accelerates sensing and seizing processes (Teece, 2007).

The absence of survey evidence on specialty-specific dynamics highlights a triangulation gap: market incentives are visible at the institutional level but not at the individual level. Market incentives therefore shape strategic attractiveness but do not substitute for foundational technological or organisational readiness.

5.2.2 Regulation as ambivalent structural boundary

Regulation featured prominently in the expert interviews but showed limited explanatory power in the survey. Experts identified the MDR and GDPR as key constraints, whereas survey respondents did not associate privacy concerns with their willingness to engage with DTs. This divergence points to a structural asymmetry: regulatory constraints shape institutional decision-making but remain largely invisible at the patient level (Greenhalgh et al., 2017).

This does not imply that regulation is irrelevant, but that its constraining effects operate primarily at the institutional decision-making level rather than at the level of individual acceptance.

5.2.3 Resource availability and infrastructural maturity

Experts consistently identified shortages in IT capacity, analytics expertise, and project management capabilities as structural barriers to DT implementation. Prior literature supports this view by positioning resources and skills as enabling conditions for complex socio-technical systems (Brommeyer et al., 2023; Kuriakose et al., 2024).

As these constraints did not emerge in the survey, resources represent a partially triangulated driver that is highly relevant at the organisational level but not reflected in patient-level attitudes. Resource capacity therefore functions as a contextual moderator, shaping how effectively primary drivers translate into implementation.

5.3 Mediating and Moderating Drivers

Individual-level factors did not emerge as primary drivers of DT adoption but shaped how technological and organisational conditions translated into acceptance-related behaviours. Rather than initiating adoption, individual attitudes mediated and moderated the strength and stability of adoption pathways. This challenges Technology Acceptance Model (TAM) interpretations that treat individual acceptance as the primary bottleneck of adoption.

5.3.1 Mediator: Openness to Digital Health

Openness toward digital health technologies primarily functioned as a resilience mechanism under conditions of uncertainty. Survey results indicate that higher openness substantially reduced trust erosion following hypothetical negative DT scenarios.

Expert interviews support this pattern by highlighting generational and specialty-specific differences. Digitally mature domains displayed greater tolerance for experimentation and early-stage imperfection. Openness therefore strengthened the translation of perceived usefulness into sustained acceptance without independently triggering adoption.

5.3.2 Mediator: Trust

Trust emerged as a conditional mediator rather than a causal driver of DT adoption. Expert interviews consistently framed trust as essential for clinician acceptance, particularly with regard to explainability and accountability.

In contrast, survey evidence revealed only weak direct effects of trust orientation on willingness to share personal health data or to demand control rights.

These findings suggest that trust in DT contexts is primarily shaped by system reliability and workflow integration rather than by stable individual dispositions. Clinicians associate trust with clinical validity and professional responsibility, while consumers treat data sovereignty as a baseline expectation largely independent of trust in DT-supported physicians. This challenges acceptance work treating trust as an antecedent and supports views linking trust to system reliability and explainability (Asan et al., 2020b; Holden & Karsh, 2010).

5.3.3 Moderator: Risk Perception Focused on Functional Reliability

Risk perception differed across analytical levels. Experts primarily emphasised regulatory, privacy, and liability risks, whereas survey respondents were mainly concerned about incorrect or biased recommendations.

These functional risks significantly reduced willingness to share personal health data, indicating that individual risk perceptions moderated perceived usefulness and trust rather than directly constraining adoption.

5.3.4 Moderator: Chronic Condition Experience as a Value Amplifier

Chronic health experience amplified perceived value. Individuals with chronic conditions consistently evaluated patient-level DTs as more useful, indicating that patient characteristics moderate value attribution even when organisational readiness remains constant.

5.4 Integrative Synthesis: What Drives Digital Twin Adoption in Healthcare?

Synthesising evidence from the literature, expert interviews, and healthcare consumer data reveals a hierarchical adoption mechanism. Across all methods, technological readiness and organisational integration consistently emerged as the primary conditions defining adoption feasibility. Interoperable data infrastructures, workflow integration, governance alignment, and leadership commitment constitute necessary foundations without which adoption rarely progresses beyond isolated pilot projects. Perceived usefulness functions as a central bridging mechanism by translating these structural conditions into clinical and operational legitimacy.

Once feasibility is established, secondary drivers such as market incentives, specialty-specific dynamics, regulation, and resource availability shape the speed and uneven distribution of adoption. Individual-level factors operate primarily as mediating and moderating mechanisms: openness stabilises acceptance under uncertainty, trust emerges from system reliability and organisational integration, and functional risk perceptions influence willingness to engage with DT-enabled services.

Overall, the findings largely corroborate prior literature in identifying technological readiness and organisational integration as core adoption conditions (Brommeyer et al., 2023; Greenhalgh et al., 2017; Kuriakose et al., 2024), while diverging from acceptance-focused models that overemphasise individual attitudes and underscoring the need for more level-sensitive adoption frameworks.

6 Conclusion

6.1 Summary of Key Findings

This thesis set out to answer the central research question: **What are key factors driving adoption of Digital Twins in healthcare?** Across all empirical components, the findings converge on a robust and methodologically triangulated conclusion: **Digital Twin adoption is primarily driven by the alignment of technological and organizational capabilities, while individual attitudes play a moderating rather than a causative role.**

The triangulation of evidence strengthens this interpretation. The literature, expert interviews, and survey data consistently demonstrate that **technological readiness**, particularly the availability of interoperable data infrastructures, reliable system integration, and mature analytics pipelines, is a necessary precondition for any substantive DT implementation. **Organizational capabilities**, including workflow integration, governance coherence, leadership sponsorship, and cross-functional collaboration, determine whether this technical potential translates into sustained practice. These factors jointly establish the structural and strategic environment in which adoption can occur.

At the same time, **perceived usefulness** emerges as a cross-cutting evaluative mechanism. Experts justify DT adoption primarily through improvements in diagnostic accuracy, risk stratification, and operational efficiency. Survey respondents, particularly those with chronic conditions or dissatisfaction with their healthcare system, attribute significantly higher perceived value to DT applications. Perceived usefulness does not operate as a purely individual attitude, but as a contextual evaluation.

This reflects the interaction between clinical needs, organisational performance, and system-level shortcomings. This indicates that usefulness is not an inherent property of DTs, but a contextual judgement shaped by clinical need, institutional performance, and personal experience. Individual-level attitudes primarily operate as **mediating** and **moderating mechanisms** that shape how capability-based drivers translate into acceptance-related behaviour.

Openness mitigates trust erosion following adverse events, functional risk concerns influence willingness to share data, and personal health experience amplifies perceived usefulness.

However, none of these factors independently determine adoption; instead, they condition the strength with which structural and capability-based drivers translate into acceptance.

Overall, adoption materialises when hospitals are technologically prepared, organisationally coordinated, and capable of translating perceived value into workflow-embedded practice. Individual acceptance reinforces, but does not replace, this institutional readiness.

6.2 Contributions to Research and Practice

6.2.1 Theoretical Contributions

This study generates three core theoretical contributions.

First, it **reconceptualises the role of individual factors in technology acceptance models**. Contrary to classical TAM assumptions, trust, openness, and risk perception do not function as primary determinants of adoption. Instead, the triangulated evidence shows that they operate as **mediators**, influencing how structural capabilities are interpreted and experienced. This reframing positions DT adoption as a system-level phenomenon rather than an aggregation of individual intentions.

Second, the study **extends and refines the TOE framework** by demonstrating that adoption cannot be explained through additive factor lists. Instead, findings show that adoption results from **capability alignment**, the interdependence of technological readiness, organisational integration, and contextualised usefulness perceptions. This shifts TOE from a descriptive model to a mechanism-oriented explanation of adoption dynamics.

Third, the research integrates **Dynamic Capabilities Theory** into **DT adoption** by conceptualising sensing, seizing, and transforming as latent organisational propensities rather than realised outcomes.

Building on Barreto's (2010) perspective, the findings illustrate how these capabilities condition adoption feasibility under uncertainty without implying direct performance effects. Taken together, these contributions offer one of the first triangulated conceptualisation of DT adoption that unifies patient-level perceptions, professional expertise, and organisational mechanisms within a single explanatory framework.

6.2.2 Practical Implications

The findings provide actionable implications for both managers and policymakers.

6.2.2.1 Managerial implications

The findings suggest a clear sequencing logic for managers. Technological readiness is a prerequisite resource condition, while organisational integration reflects a strategic choice about how resources are combined and deployed.

Individual acceptance functions as a reinforcing mechanism rather than a primary driver. DT adoption cannot be achieved through technology acquisition alone. It requires deliberate organisational transformation and cross-functional governance connecting IT, clinical departments, and analytics teams.

The most robust "right" choices prioritise interoperability, data quality, and real-time data flows, whereas isolated DT investments under persistent fragmentation are unlikely to scale sustainably. Workflow integration and clear decision rights determine whether DTs reduce rather than increase cognitive load in clinical routines. Segment-specific strategies are advisable: patients with chronic conditions reported higher perceived usefulness and are suitable early adopters for targeted pilot implementations before broader scaling.

6.2.2.2 Policy implications

For policymakers, the results indicate that institutional and regulatory conditions shape adoption more strongly than patient attitudes. Regulatory pathways for model-based and simulation-based technologies should be clarified and harmonised to reduce uncertainty. Reimbursement schemes need to shift toward value-based incentives that reward predictive accuracy, improved outcomes, and operational efficiency. National interoperability standards and robust data-governance frameworks are essential for scalability. Governance mechanisms should prioritise transparency, explainability, and auditability, addressing concerns related to algorithmic reliability rather than privacy alone.

6.3 Limitations and Future Research Directions

6.3.1 Limitations

6.3.1.1 Literature Review

The review prioritised recent academic and industry sources, which may underrepresent regional or emerging grey literature. Variations in DT definitions limit conceptual comparability, and the integration of multiple theoretical frameworks introduces potential interpretation bias.

6.3.1.2 Expert Interviews

While diverse, the expert sample reflects predominantly digitally mature institutions, limiting transferability to lower-resourced settings. Qualitative findings are context-dependent and shaped by theoretical framing and researcher interpretation, constraining generalisability. The strong representation of digitally mature institutions may bias findings toward feasibility-oriented perspectives and underrepresent barriers faced by lower-resourced settings.

6.3.1.3 Survey Component

The non-probability, online convenience sample resulted in a digitally literate, younger, and highly educated respondent group, reducing representativeness. Key constructs were measured with single items, restricting reliability. The cross-sectional design captures attitudes at one moment and cannot assess temporal dynamics. Self-selection bias and data-quality filters may additionally have influenced the distribution of responses.

6.3.2 Future Research Directions

Building directly on the findings of this study, future research should extend the Adoption Driver Framework along three dimensions. First, empirical research should examine how sensing, seizing, and transforming propensities develop over time during DT implementation with particular attention to how governance and workflow redesign enable the transition from pilot implementations to institutionalise use.

Second, longitudinal studies should analyse how trust, openness, and functional risk perception evolve during real-world deployment, distinguishing stabilising mediators from short-term acceptance effects. Third, future research should investigate how regulatory interpretation, certification, and reimbursement interact with organisational capabilities, as regulatory barriers primarily affect institutional decision-making rather than patient acceptance.

References

Airehenbuwa, B., Hasan, T., Sarkar, S., & Guin, U. (2025). *Advancing Security with Digital Twins: A Comprehensive Survey* (No. arXiv:2505.17310). arXiv. https://doi.org/10.48550/arXiv.2505.17310

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial Intelligence and Human Trust in Healthcare: Focus on Clinicians. *Journal of Medical Internet Research*, *22*(6), e15154. https://doi.org/10.2196/15154

Barney, J. B., Ketchen, D. J., & Wright, M. (2021). Resource-Based Theory and the Value Creation Framework. *Journal of Management*, *47*(7), 1936–1955. https://doi.org/10.1177/01492063211021655

Barreto, I. (2010). Dynamic Capabilities: A Review of Past Research and an Agenda for the Future. *Journal of Management*, *36*(1), 256–280. https://doi.org/10.1177/0149206309350776

Brommeyer, M., Whittaker, M., Mackay, M., Ng, F., & Liang, Z. (2023). Building health service management workforce capacity in the era of health informatics and digital health – A scoping review. *International Journal of Medical Informatics*, *169*, 104909. https://doi.org/10.1016/j.ijmedinf.2022.104909

Capacho-Alfonso, V. H., Soto-Durán, D. E., & Jiménez-Builes, J. A. (2025). Health technology adoption model for big data integration in hospitals: A systematic approach in the era of health 4.0. *Health Services and Outcomes Research Methodology*, *25*(4), 410–437. https://doi.org/10.1007/s10742-025-00345-w

Christensen, C. M. (2008). *The innovator's dilemma: When new technologies cause great firms to fail* (Rev., updated, and with a new chapter, [Nachdr.]). Harvard Business School Press.

Christensen, C. M., Grossman, J. H., & Hwang, J. (2009). *The innovator's prescription: A disruptive solution for health care*. McGraw-Hill.

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (Third edition). SAGE.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%253C1105::AID-SMJ133%253E3.0.CO;2-E

Erol, T., Mendi, A. F., & Dogan, D. (2020). The Digital Twin Revolution in Healthcare. *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 1–7. https://doi.org/10.1109/ISMSIT50672.2020.9255249

Glaessgen, E., & Stargel, D. (2012, April 23). The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. *53rd AIAA/ASME/ASCE/AHS/ASC* Honolulu, Hawaii. https://doi.org/10.2514/6.2012-1818

Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., A'Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond Adoption: A New Framework for Theorizing and Evaluating Nonadoption, Abandonment, and Challenges to the Scale-Up, Spread, and Sustainability of Health and Care Technologies. *Journal of Medical Internet Research*, *19*(11), e367. https://doi.org/10.2196/jmir.8775

Grieves, M. (2014). Digital Twin: Manufacturing Excellence through Virtual Factory Replication. *Digital Twin White Paper*, 7.

Guest, G., Bunce, A., & Johnson, L. (2006). How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Han, Y., Li, Y., Li, Y., Yang, B., & Cao, L. (2023). Digital twinning for smart hospital operations: Framework and proof of concept. *Technology in Society*, *74*, 102317. https://doi.org/10.1016/j.techsoc.2023.102317

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine*, *292*, 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

Kleinbeck, C., Zhang, H., Killeen, B. D., Roth, D., & Unberath, M. (2024). Neural digital twins: Reconstructing complex medical environments for spatial planning in virtual reality. *International Journal of Computer Assisted Radiology and Surgery*, *19*(7), 1301–1312. https://doi.org/10.1007/s11548-024-03143-w

Kuriakose, S. M., Joseph, J., A, R., & Kollinal, R. (2024). The Rise of Digital Twins in Healthcare: A Mapping of the Research Landscape. *Cureus*. https://doi.org/10.7759/cureus.65358

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry* (Nachdr.). Sage.

Lu, Y., Liu, C., Wang, K. I.-K., Huang, H., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing*, *61*, 101837. https://doi.org/10.1016/j.rcim.2019.101837

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

MarketsandMarkets. (2025). Digital Twins in Healthcare Market: Growth, Size, Share, and Trends. *By Markets and Markets*, *May, 2025*. https://www.marketsandmarkets.com/Market-Reports/digital-twins-in-healthcare-market-74014375.html

Mayring, P. (2015). *Qualitative Inhaltsanalyse: Grundlagen und Techniken* (13., überarbeitete Auflage). Beltz.

OECD. (2025). *Health at a Glance 2025: OECD Indicators*. OECD Publishing. https://doi.org/10.1787/8f9e3f98-en

Olsson, U. (2022). *Power Properties of Ordinal Regression Models for Likert Type Data*. https://doi.org/10.7275/ER28-5992

Pai, F.-Y., & Huang, K.-I. (2011). Applying the Technology Acceptance Model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, *78*(4), 650–660. https://doi.org/10.1016/j.techfore.2010.11.007

Patton, M. Q. (2015). Sampling, Qualitative (Purposeful). In G. Ritzer (Hrsg.), *The Blackwell Encyclopedia of Sociology* (1. Aufl.). Wiley. https://doi.org/10.1002/9781405165518.wbeoss012.pub2

Porter & Lee. (2013). The Strategy That Will Fix Health Care. *Harvard Business Review*.

Porter, M. E., & Teisberg, E. O. (2006). *Redefining Health Care: Creating Value-based Competition on Results*. Harvard Business Review Press.

Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., Wang, L., & Nee, A. Y. C. (2021). Enabling technologies and tools for digital twin. *Journal of Manufacturing Systems*, *58*, 3–21. https://doi.org/10.1016/j.jmsy.2019.10.001

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2019). Diffusion of Innovations 1. In D. W. Stacks, M. B. Salwen, & K. C. Eichhorn (Hrsg.), *An Integrated Approach to Communication Theory and Research* (3. Aufl., S. 415–434). Routledge. https://doi.org/10.4324/9780203710753-35

Sadée, C., Testa, S., Barba, T., Hartmann, K., Schuessler, M., Thieme, A., Church, G. M., Okoye, I., Hernandez-Boussard, T., Hood, L., Shmulevich, I., Kuhl, E., & Gevaert, O. (2025). Medical digital twins: Enabling precision medicine and medical artificial intelligence. *The Lancet Digital Health*, *7*(7), 100864. https://doi.org/10.1016/j.landig.2025.02.004

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Sun, T., He, X., & Li, Z. (2023). Digital twin in healthcare: Recent updates and challenges. *DIGITAL HEALTH*, *9*, 20552076221149651. https://doi.org/10.1177/20552076221149651

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital Twin in Industry: State-of-the-Art. *IEEE Transactions on Industrial Informatics*, *15*(4), 2405–2415. https://doi.org/10.1109/TII.2018.2873186

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%253C509::AID-SMJ882%253E3.0.CO;2-Z

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation* (4. print). Lexington Books.

Vallée, A. (2023). Digital twin for healthcare systems. *Frontiers in Digital Health*, *5*, 1253050. https://doi.org/10.3389/fdgth.2023.1253050

Viceconti, M., De Vos, M., Mellone, S., & Geris, L. (2024). Position Paper From the Digital Twins in Healthcare to the Virtual Human Twin: A Moon-Shot Project for Digital Health Research. *IEEE Journal of Biomedical and Health Informatics*, *28*(1), 491–501. https://doi.org/10.1109/JBHI.2023.3323688

Yu, D., & Hang, C. C. (2010). A Reflective Review of Disruptive Innovation Theory. *International Journal of Management Reviews*, *12*(4), 435–452. https://doi.org/10.1111/j.1468-2370.2009.00272.x

Appendices

Appendix A: Expert Interview guides

Appendix A.1: Interview guide – Expert group Consultants

No.	Question Block	Guiding Questions
1	**Market and Technology Perception**	• How do you assess the overall maturity and market potential of data-driven or Digital Twin technologies in healthcare? • Which trends or technological developments are currently shaping digital health projects (e.g., AI, analytics, process mining, data platforms)? • In which areas do you observe the strongest demand or openness to data-driven innovation (clinical vs. operational use cases)? • To what extent do new technologies (Digital Twins, simulation, predictive models) already influence strategic discussions?
2	**Organizational and Implementation Factors**	• What organizational prerequisites are necessary for successful implementation (leadership support, digital strategy, governance)? • How do hospitals typically handle cross-functional collaboration between IT, clinicians, management, and industry partners? • What are the most common barriers in data-driven transformation projects (silos, data quality, lack of ownership, staffing constraints)? • How important are change management, communication, and internal champions for adoption? • Where do implementation efforts most often fail in practice?
3	**Strategic and Economic Logic / Value Creation**	• Which decision criteria drive investments in data-driven technologies (efficiency, quality improvement, competitiveness, innovation profile)? • How relevant are ROI, business cases, or proof-of-value results in securing executive buy-in? • How can the value contribution of Digital Twins be articulated (clinical precision, patient outcomes, process stability, cost reduction)? • What differentiates successful from unsuccessful digital investment decisions?
4	**Regulatory and External Environment**	• How do regulatory frameworks (GDPR/DSGVO, MDR, EU AI Act, national policies) influence the ability to implement data-driven solutions? • What role do funding programmes or public incentives play in driving adoption? • Which external constraints, such as interoperability standards, procurement processes, or data governance, act as bottlenecks? • How do hospitals and consulting projects deal with privacy, compliance, and legal uncertainties?
5	**Managerial and Strategic Perspective**	• How should leadership teams position data-driven innovation strategically within their organizations? • What managerial capabilities (e.g., vision, prioritization, digital literacy, transformation capacity) enable successful scaling? • Which collaboration or partnership models support long-term value creation in digital health (co-creation, pilots, ecosystem partnerships)? • How do you expect data-driven healthcare solutions, including Digital Twins, to evolve in the next 5–10 years? • What initial steps should a healthcare organization take when exploring Digital Twins for the first time?

Table 13: *Interview guide Consultants*

Appendix A.2: Interview guide – Expert group Physicians

No.	Question Block	Guiding Questions
1	**Perception & Usefulness**	• How would you situate the concept of a *Digital Twin* within your clinical practice or specialty? • In which areas of your everyday work do you already encounter digital models, simulations, or AI-supported tools that could be considered early forms of Digital Twins? *(e.g., diagnostic imaging, treatment planning, risk prediction, monitoring)* • Which clinical applications do you consider realistically achievable in the next years? *(e.g., personalized therapy simulations, disease progression forecasting, procedure planning)* • Where do you personally see the greatest added value of such systems?
2	**Everyday Integration**	• What would need to work smoothly in your daily routines for a Digital Twin to be practical and helpful? • Have you already used AI-based or simulation-supported tools in your work? How would you describe these experiences? • What would most likely prevent you from using such a system regularly? *(e.g., time pressure, trust, technical limitations, workflow disruptions)* • What type of output, visualization, or feedback would be most valuable to you during diagnosis, treatment, or follow-up?
3	**Collaboration & Environment**	• What kind of training or support would help you feel confident using Digital Twin technologies? • Which professional groups should be involved in the implementation process? *(IT, nursing staff, clinical management, medical leadership, quality management)* • Which external factors, such as data protection, reimbursement structures, regulation, or guidelines, do you think influence whether such technologies are adopted? • What organizational or structural barriers might hinder the introduction of Digital Twins in your hospital or department?
4	**Organizational & Managerial View**	• To what extent does successful implementation depend on support from hospital leadership or department heads? • What would you expect from your leadership team to facilitate the integration of new digital solutions? • What role should medical associations or professional societies play in evaluating, certifying, or standardizing Digital Twin technologies?
5	**Personal Perspective & Outlook**	• If you could design the *ideal Digital Twin* for your specialty, what would it include or be able to do? • What would need to happen for you to say: *"I want to try this in my daily work.", "I would use this regularly."*

Table 14: *Interview guide Physicians*

Appendix A.3: Interview guide – Expert group Hospital Management

No.	Question Block	Guiding Questions
1	**Technological Readiness & Infrastructure**	• How would you describe the current level of digital maturity and data readiness at your hospital or within university hospitals in general? • Which technical infrastructures are already in place (interoperability, networking, data platforms), and which ones are still missing to enable advanced systems such as Digital Twins? • How relevant are IT security standards and cybersecurity requirements for implementing such innovations? • In which operational or clinical areas do you see the strongest potential value for Digital Twin applications?
2	**Organizational & Governance Factors**	• What organizational prerequisites are necessary to successfully introduce Digital Twin or other advanced data-driven systems? *(alignment between IT, clinical staff, administration, and top management; governance; coordination mechanisms)* • How important is change management when implementing new digital or data-driven technologies in a hospital environment? • How do you personally navigate trust, acceptance, and responsibility when introducing new digital tools? • Are there governance structures or internal processes at your institution that support data protection and cybersecurity during innovation projects?
3	**Individual & Cultural Aspects**	• How would you describe the attitude of staff, clinicians, nurses, administrative teams, towards data-driven technologies? • Do you observe more openness or scepticism, particularly among physicians and nursing staff? • What role does trust, both in the technology and in the IT department, play in adoption? • Which competencies or training formats do you consider necessary to enable staff to work safely and effectively with Digital Twin technologies?
4	**Environmental & Regulatory Conditions**	• How do you evaluate the current regulatory framework for digital health solutions in your country? *(data protection laws, medical device regulation, cybersecurity requirements)* • In your view, do these regulations support innovation, or do they sometimes hinder implementation? • What role do external partners: MedTech companies, software providers, research institutions play in implementing secure and effective Digital Twin solutions? • Are there collaboration models that you consider particularly suitable for hospitals?
5	**Strategic Perspective & Future Outlook**	• How do you assess the future role of Digital Twins in hospital operations? *(occasional niche use vs. central element of clinical and administrative management)* • From your perspective, what are the key strategic opportunities and risks associated with the adoption of Digital Twin technologies? • If you had to give three recommendations for the safe, sustainable, and value-oriented implementation of data-driven systems in hospitals, what would they be? • What would need to happen for Digital Twins to become part of the hospital's long-term digital strategy?

Table 15: *Interview guide Hospital Management*

Appendix A.4: Interview guide – Expert group MedTech Professionals

No.	Question Block	Guiding Questions
1	**Market Understanding & Digital Twin Relevance**	• How would you describe the current maturity and demand for data-driven technologies in your core clinical markets? • Which trends are most influential in driving interest in simulation-based or Digital Twin–like solutions? • In what ways does your current product portfolio already incorporate elements of virtual models or workflow simulations? • Which customer segments (e.g., university hospitals, private groups, outpatient centers) show the highest openness toward such technologies? • What factors most strongly shape your customers' willingness to adopt Digital Twin concepts?
2	**Implementation Requirements & Adoption Barriers**	• What technical and organizational prerequisites must hospitals meet to effectively use model-based or simulation-supported systems? • Which integration challenges: data quality, interoperability, infrastructure do you encounter most often? • Where do implementations typically fail, and what are common "deal breakers"? • What influences end-user acceptance the most, especially among clinicians or technical staff? • Which aspects of workflow fit, or usability determine whether a solution becomes part of daily clinical practice?
3	**Partnerships & Collaboration With Hospitals**	• How do you usually structure collaborations with hospitals (pilots, co-development, clinical studies, strategic partnerships)? • What characteristics distinguish highly successful partnerships from less successful ones? • How do you balance speed of innovation with hospitals' needs for safety, validation, and regulatory compliance? • What forms of feedback or co-creation from hospitals are most valuable during product development? • How do you build and maintain trust regarding data usage, reliability, and long-term system integration?
4	**Value Creation & Business Models**	• What concrete value propositions resonate most strongly with hospitals considering Digital Twin–related solutions? • Which outcomes: efficiency, quality, predictability, cost savings are most important to hospital leadership? • Which business models (SaaS, subscription, CapEx, pay-per-use, bundled services) have proven most effective in your market? • How do hospitals generally respond to recurring cost structures or long-term subscription commitments? • What evidence or metrics do hospitals expect to justify investment in Digital Twin–like technologies?
5	**Regulatory Environment & Strategic Outlook**	• How do current regulatory developments (MDR, EU AI Act, data protection laws) impact your product strategy? • Which regulatory requirements create the biggest barriers for scaling digital, model-based technologies? • How do you ensure compliance while still maintaining innovation speed and market competitiveness? • Which external factors (procurement cycles, reimbursement structures, certification processes) influence adoption the most? • Looking ahead 5–10 years, where do you see the strongest potential for Digital Twins, and what must happen for broad implementation?

Table 16: *Interview guide MedTech Professionals*

Appendix A.5: Interview guide – Expert group Academic Researchers

No.	Question Block	Guiding Questions
1	**Technological & System Readiness**	• How would you assess the current maturity of data-driven simulation and Digital Twin technologies within healthcare systems today? • Which clinical or operational domains do you consider most promising for meaningful value creation (e.g., predictive diagnostics, system planning, patient-flow modelling)? • What are the key technological dependencies that determine feasibility? • From a systems perspective, how prepared are European health systems to incorporate Digital Twins into existing digital infrastructures such as national health data spaces?
2	**Organizational & Managerial Capabilities**	• Which organizational capabilities are essential for hospitals to adopt Digital Twin technologies successfully • How can healthcare organizations manage the tension between innovation and operational constraints such as cost, workflow disruption, and trust? • In your academic and policy experience, how critical is strong leadership commitment for digital innovation in healthcare? • Are there organizational models or case examples that illustrate how capacity for innovation can be built sustainably?
3	**Environmental, Regulatory & Policy Factors**	• How would you evaluate the current regulatory and policy landscape (AI Act, EHDS, MDR, GDPR) in relation to Digital Twin development and adoption? • Do these frameworks generally enable innovation, or do they create friction and where specifically? • How important are regulatory clarity and standardization for fostering trust and responsible use of simulation-based decision support systems? • What should governments and policymakers prioritize to support Digital Twin adoption while maintaining ethical, privacy, and safety standards?
4	**Strategic, Value & System-Level Perspectives**	• How can Digital Twin technologies contribute to the broader goals of Value-Based Healthcare and system efficiency? • What types of long-term value: beyond pilot success can Digital Twins generate for healthcare systems and policymakers? • Do you believe Digital Twins can evolve into structural components of healthcare planning, or will they remain specialized tools? • What governance or leadership models need to evolve for Digital Twins to become embedded rather than isolated research initiatives?
5	**Future Outlook, Culture & Critical Reflection**	• Which Digital Twin use cases do you consider realistic, and which are currently overestimated in public and industry discourse? • What technical, organizational, and regulatory conditions must be met to move Digital Twins from research prototypes to clinical routine? • Are there blind spots or misconceptions in current Digital Twin discussions that academic research should address? • If you were advising key decision-makers on responsible acceleration of Digital Twin adoption, what would be your three core recommendations?

Table 17: *Interview guide Academic Researchers*

Appendix B: Expert Interview Summaries

Appendix B.1 Expert Interview Summary E01 (Consultant)

1. Market and Technology Perception

Expert E01 emphasized a strong divergence between the scientific maturity of Digital Twin technologies and the limited practical readiness of German hospitals. She observed that hospitals currently prioritize efficiency-driven innovations due to severe financial pressure, increasing patient volumes, and demographic challenges. As a result, Digital Twin applications that improve resource allocation, patient flow, or operational performance have significantly higher adoption potential than organ-level models aimed purely at quality enhancement. E01 noted that preventive and predictive applications could also gain traction, particularly if they reduce long-term treatment costs. Overall, she perceived Digital Twins as conceptually valuable but misaligned with the immediate priorities of most German hospitals.

2. Organizational and Implementation Factors

According to E01, the implementation of Digital Twins is constrained by a combination of organizational hierarchies and substantial data-infrastructure gaps. She highlighted the decisive role of senior clinical leaders, especially chief physicians as adoption champions capable of aligning IT and executive decision-makers. However, hospitals often lack project management capacity to coordinate complex digital initiatives. Technically, she reported three core blockers: fragmented IT systems, absence of semantic harmonization, and widespread unstructured clinical documentation, which make real-time data pooling and simulation nearly impossible in current environments. E01 stressed that without a consolidated and harmonized data foundation, advanced modelling technologies cannot be introduced meaningfully.

3. Strategic and Economic Logic / Value Creation

E01 stated that the dominant strategic lens in German hospitals is cost containment, not digital transformation or quality-oriented innovation. Technologies are evaluated primarily on their ability to reduce cost per case or improve throughput. She observed that Digital Twin solutions capable of demonstrating clear economic benefits: efficiency gains, reduced waste, or fewer avoidable treatments would receive the strongest executive attention. Conversely, clinically focused Digital Twins were described as “nice-to-have” but strategically deprioritized.

She also suggested that the consumer market may adopt Digital Twin-like tools faster than hospitals, as individuals increasingly collect health data through wearables, diagnostics, and longevity products.

4. Regulatory and External Environment

E01 described Germany’s regulatory environment, especially data protection (GDPR/DSGVO), as a substantial barrier that slows exploration of advanced data-driven technologies. She contrasted this with Scandinavian countries, which she perceives as more pragmatic in their interpretation of European privacy laws and therefore better positioned for Digital Twin development. While public funding schemes (e.g., KHZG) can accelerate adoption, she noted that many hospitals treat these programs primarily as procurement opportunities rather than strategic transformation levers. She emphasized that meaningful usage requirements and long-term integration criteria are necessary to avoid isolated, low-impact digital purchases.

5. Managerial and Strategic Perspective

E01 described hospital leadership as predominantly operationally oriented, prioritizing stability, efficiency, and risk minimization. Only a minority of institutions, mainly large university hospitals, adopt a forward-looking digital strategy. She emphasized the importance of key user networks and internal opinion leaders to drive change, as clinicians are most influenced by trusted peers. Cultural complexity, highly heterogeneous staff groups, and limited experimentation space make change management considerably more challenging than in corporate settings. E01 sees consultancies playing an important role as strategic translators and coordinators, helping hospitals clarify use cases, align stakeholders, and build the data foundations required for advanced technologies such as Digital Twins.

Important Quotes

- "Hospitals are so overloaded that they do not need quality optimisation, they need efficiency at every corner."
- "In the end, nobody benefits because the data is not semantically harmonised." "What works well is everything that can shorten throughput times."
- "Hospitals are currently so overwhelmed that they focus strongly on efficiency and far less on quality."
- "I always look much more at what I actually experience inside the hospital."

Appendix B.2 Expert Interview Summary E02 (Consultant)

1. Market and Technology Perception

Expert E02 emphasized that the relevance and adoption potential of data-driven and AI technologies differ strongly across healthcare actors. In Pharma and Life Sciences, she sees broad applicability across the entire value chain, including drug discovery, molecule simulation, clinical trial optimization, supply chain resilience, and commercialization via AI-enabled physician portals. In hospitals, current priorities are heavily operational: workflow optimization, scheduling, documentation automation, and patient safety alerts matter more than highly advanced clinical modelling. Insurers focus primarily on claims automation, risk prediction, and improved customer communication. Across all segments, she noted a clear trend toward personalization, automation, and predictive analytics, but with substantial variation in maturity and readiness.

2. Organizational and Implementation Factors

E02 highlighted that successful implementation depends first on establishing a basic technological and data foundation, particularly in hospitals, where fragmented IT, outdated systems, and inconsistent data formats are still widespread. She identified IT competencies, talent availability, and clear user-centred design processes as central enablers. Cultural barriers were described as equally important: staff often fear redundancy or lack confidence in using new systems. She noted that user adoption is frequently underestimated, and many health organizations introduce too many tools without proper onboarding, training, or communication. She described data quality, regulatory uncertainty, siloed mindsets, and slow decision-making as recurrent implementation barriers across all healthcare actors.

3. Strategic and Economic Logic / Value Creation

According to E02, digital innovation is only adopted when a clear and quantifiable business case is established. Hospitals, Pharma firms, and MedTech clients all require strong evidence of cost savings, risk reduction, or commercial upside. She explained that Digital Twin–like tools gain traction when they support top-line growth (new customers, new markets) or bottom-line improvements (efficiency, fewer technician visits, predictive maintenance). Strategic clarity and prioritization are essential; organizations face numerous potential use cases but risk diluting resources if they pursue too many in parallel. For this reason, she sees focused innovation pathways and explicit value narratives as critical to avoid “pilot fatigue” and ensure long-term strategic relevance.

4. Regulatory and External Environment

E02 described regulatory complexity as a consistent barrier across markets. While Germany’s environment is strict, she sees similar protectionist tendencies globally, citing China’s requirement for domestic technology stacks as an example of increasing national fragmentation. She emphasized that AI or Digital Twin development in Pharma and MedTech must comply with stringent Medical Device Regulation (MDR), safety evaluation, and data-protection rules. She argued that large-scale pilots are often infeasible because any patient-facing digital tool must undergo extensive approval, limiting experimentation and slowing innovation cycles. Funding programs can help, but only when tied to meaningful infrastructure improvements rather than isolated purchasing decisions.

5. Managerial and Strategic Perspective

E02 described leadership capabilities as decisive for scaling data-driven solutions. She highlighted the need for agile ways of working, cross-functional collaboration, tolerance for failure, and the ability to prioritize and focus. Traditional hierarchical structures and siloed teams hinder rapid progress, particularly in hospitals where operational pressure dominates. She emphasized the importance of starting with small lighthouse projects to build confidence, demonstrate value quickly, and reduce resistance. Time was identified as a major structural constraint: day-to-day operations leave little room for strategic innovation, meaning that long, multi-year transformation programs often lose momentum. She argued that managers must champion a learning culture, enable cross-organizational cooperation, and foster openness to iterative development.

Important Quotes

- “The relevance of data-driven technologies varies significantly across the healthcare sector; hospitals focus more on operational workflows than on advanced clinical modelling.”
- “Many organizations underestimate user adoption; they introduce too many digital tools without proper onboarding or communication.”
- “Digital innovation only gets adopted when there is a clear and quantifiable business case.”
- “Regulatory complexity is a consistent barrier, and large-scale pilots are often impossible because anything patient-facing requires extensive approval.”
- “Leadership is decisive, without cross-functional collaboration, tolerance for failure, and clear prioritization, digital projects lose momentum.”

Appendix B.3 Expert Interview Summary E03 (Consultant)

1. Market and Technology Perception

Expert E03 described Digital Twins as valuable but currently limited by cost and system complexity. He emphasized that full-scale hospital or patient-level twins remain expensive and still depend heavily on the maturity of AI, big data infrastructures, and visualization technologies. Over the past decade, he observed a shift from classical simulation tools to more sophisticated and increasingly accessible software, including open-source options. He noted that the strongest adoption momentum lies in process optimization, where time-based modelling aligns closely with hospital performance indicators such as wait times, throughput, and resource utilization. Clinical Digital Twins are emerging but still face significant data and system-readiness challenges. Overall, he sees demand concentrated on use cases with clear operational and financial impact.

2. Organizational and Implementation Factors

E03 highlighted that implementation success depends on institutional scope and data availability. Larger healthcare systems derive more value because Digital Twins can map complex, multi-step processes where interdependencies become visible. Smaller clinics often lack influence over upstream and downstream processes, limiting their ability to act on model insights. He identified institutional complexity, data privacy constraints, and inconsistent data access as early blockers. Successful implementations require clear governance around data use, consistent stakeholder communication to alleviate fears of job loss or surveillance, and strong alignment between strategic planning cycles and model updates. He emphasized that Digital Twins are only sustainable if hospitals invest in maintaining models, updating data inputs, and upskilling internal teams.

3. Strategic and Economic Logic / Value Creation

According to E03, the primary driver of adoption is return on investment, particularly reductions in waiting times, improved resource utilization, and avoidance of downtime. He noted that Digital Twins are most effective in environments where time equates directly to financial value, either through reduced public expenditures or increased operational efficiency. He distinguished between one-off strategic projects (e.g., hospital redevelopment) and continuous optimization programs, explaining that the business case must be explicit for both.

He also noted that the economic logic differs between public and private systems: private systems evaluate Digital Twins through hard-dollar gains, while public systems prioritize blended metrics that include qualitative patient outcomes and service accessibility.

4. Regulatory and External Environment

E03 described regulatory and data governance frameworks as major determinants of where Digital Twins flourish. He contrasted Canada, where data flows more systematically through provincial and national structures, with the United States, where data remains proprietary and fragmented, making cross-organization modelling difficult. He emphasized that privacy laws, data-sharing rights, and community expectations shape adoption curves in every region. Before initiating a Digital Twin project, his team evaluates data access rights, anonymization rules, and the organization’s ability to use patient data for business or community-level decisions.

He underscored the need for clear policies to reassure staff and patients that data is used responsibly and not for staff reduction or punitive decision-making.

5. Managerial and Strategic Perspective

E03 emphasized that Digital Twins are typically positioned as enablers within large transformation efforts, such as service redesign, infrastructure planning, or system-wide optimization. Leadership commitment is the single strongest predictor of sustained success; without senior executives who understand the strategic value of data and analytics, investments lose momentum. He stressed the importance of communicating impact continuously, not only through numbers but through narrative framing that connects model insights to patient value and system performance. He also noted that healthcare leaders must balance immediate staffing needs with long-term digital investments, requiring a mindset shift toward system-wide thinking. Looking forward, he expects Digital Twins to converge increasingly with AI, potentially becoming background components of broader AI-driven decision-support tools.

Important Quotes

- “Digital twins are expensive, so adoption always hinges on where you get the most return on investment.”
- “The wider the scope of your digital twin, the better decisions you can make. Small clinics are always at the mercy of upstream or downstream processes.”
- “Time is money, shorter time through the system means less cost and better use of resources.”

Appendix B.4 Expert Interview Summary E04 (Consultant)

1. Market and Technology Perception

Expert E04 assessed the current maturity of Digital Twin applications in healthcare as very low, describing them as closer to research concepts than operational tools. He noted that hospitals already perform activities resembling Digital Twins, such as digital process mapping or patient-journey modelling but do not label them as such. He highlighted a major divide between administrative and clinical processes: administrative workflows have strong potential because they resemble use cases from more advanced industries like logistics, whereas clinical Digital Twins depend on new-generation hospital information systems that are only now emerging. Overall, he sees significant long-term potential but limited short-term readiness.

2. Organizational and Implementation Factors

E04 emphasized that Digital Twins are not technical projects, but “at least 50% clinical and organisational change.” Success depends on early and structured involvement of physicians, nurses, and administrative users. He stressed that hospitals must free up staff capacity, because overloaded clinical teams cannot meaningfully participate without explicit protection of their time. He pointed to persistent problems with data quality, heterogeneous IT landscapes, lack of data governance, and cultural norms that treat data management as an IT-only task. He highlighted that users often resist changes that add steps to their workflow and may not understand downstream consequences of poor data entry.

3. Strategic and Economic Logic / Value Creation

E04 explained that hospitals adopt data-driven technologies primarily to increase process efficiency, reduce errors, and support better clinical decision-making. The three fundamental value drivers are: improving treatment quality, reducing errors caused by missing information, and improving the economic situation of the hospital through cost savings or revenue improvements. He stressed that many hospitals "run into implementation too quickly" without a sufficient strategy phase, which leads to timelines exploding, unclear goals, and uncontrolled resource use. He noted that return-on-investment thinking is far more pronounced in private hospitals than in public ones.

4. Regulatory and External Environment

E04 identified data protection and public procurement law as major external barriers.

He described German data-protection culture as "overbearing and prevention-oriented," frequently shutting down innovation with blanket objections. EU procurement rules slow projects by requiring long formal tender processes even when the relevant solutions are obvious. He highlighted the "Krankenhauszukunftsgesetz" (KHZG) as an important accelerator, though with limited penalties and inconsistent uptake. He believes regulatory frameworks significantly shape the feasibility and speed of Digital Twin use cases.

5. Managerial and Strategic Perspective

E04 pointed to hierarchical structures, siloed thinking, and unwillingness to collaborate across departments as persistent challenges. He emphasized that successful digital transformation requires leadership commitment, interdisciplinary governance structures, and active translation between clinical, IT, and administrative perspectives. He highlighted that many hospitals underestimate the cultural and communication components of transformation, particularly the fears and uncertainty among staff with low digital affinity. He sees Digital Twins as becoming more relevant over the next 5–10 years, accelerated by major hospital information system replacements and increasing pressure to modernize operations.

Important Quotes

- "There are developments that go in that direction, but no one in hospitals actually labels it as Digital Twin technology."
- "These digital projects are not technical projects at least fifty percent of it is clinical and organisational work."
- "In principle, there are only three goals: better treatment quality, fewer errors from missing information, or earning or saving one euro."
- "Data protection is completely overboard; it has turned into a culture of preventing things rather than enabling them."
- "Hospitals run far too quickly into implementation; without a proper strategy phase, these projects run off the rails."

Appendix B.5 Expert Interview Summary E05 (Physician)

1. Perception & Usefulness

Expert E05 described Digital Twins as a natural extension of existing digital tools in orthopedics and trauma surgery. He already uses 3D reconstruction, CT-based preoperative planning, navigation systems, and real-time intraoperative positioning tools, systems he views as "early precursors" of true Digital Twins. He sees the highest value in preoperative simulation, allowing surgeons to evaluate anatomical variants, screw placement, implant size, and surgical access routes before entering the operating room. He also expects Digital Twins to become relevant for fracture healing prediction, load distribution analysis in implants, and personalized rehabilitation timelines. While he considers many elements already present in daily practice, he stresses that current tools are not yet dynamic or continuously learning.

2. Everyday Integration

E05 emphasized that the decisive factors for adoption in clinical routines are time, workflow fit, and reliability. A Digital Twin must integrate seamlessly into existing systems such as PACS and planning software, without manual data export or complex setup steps. Any solution requiring more than a few minutes will be rejected in the operating room environment. He pointed out that data quality, system stability, and intuitive visualizations determine whether clinicians trust and consistently use such tools. He welcomed AI-based assistants but noted that systems must think "clinically," meaning they deliver prioritized, relevant, and actionable insights rather than raw data.

3. Collaboration & Environment

E05 highlighted the importance of interdisciplinary collaboration for successful implementation. He prefers short, case-based training sessions led by individuals who understand both IT and clinical workflows. He emphasized that surgical teams, OR management, and nursing staff must be involved early to avoid workflow disruptions. He identified interoperability as a major barrier, as hospitals often rely on heterogeneous IT systems that do not communicate effectively. He also noted that privacy concerns and the lack of reimbursement pathways slow down adoption, as digital planning is often perceived as uncompensated extra work.

4. Organizational & Managerial View

According to E05, the introduction of new digital tools depends heavily on explicit support from hospital and department leadership. Without managerial backing, neither budget nor time resources are allocated, and staff engagement remains low. He called for strategic prioritization, dedicated responsibilities, and pilot phases that allow iterative learning before large-scale rollouts. Professional societies play an important role in validating technologies, defining quality standards, and reducing uncertainty by offering evidence-based guidance on new digital solutions.

5. Personal Perspective & Outlook

E05's ideal Digital Twin would be patient-specific, learning, and fully integrated into the hospital's digital infrastructure. It would allow him to simulate surgical scenarios, optimize implant choices, and monitor postoperative healing trajectories in real time. He would adopt such technology immediately if it demonstrably saves time, increases surgical safety, and provides clinically meaningful recommendations.

He stressed that surgeons are not resistant to innovation; they simply need solutions that create tangible benefits for patients and operators without adding workload.

Important Quotes

- "In daily routine we already work with many digital models that are precursors of Digital Twins, even if they are not dynamic enough to be true twins."
- "Time is the limiting factor, if a system needs more than a few minutes or manual steps, it simply won't be used."
- "The biggest hurdle is missing interoperability; different systems don't speak the same language."
- "Without support from the leadership, nothing moves forward, neither financially nor organizationally."
- "If a system clearly saves time, delivers clinically relevant information, and works reliably, I would use it immediately."

Appendix B.6 Expert Interview Summary E06 (Hospital Management)

1. Technological Readiness & Infrastructure

Expert E06 assessed the digital maturity of German university hospitals as significantly below what would be required for fully functional Digital Twins. He described highly fragmented, historically grown IT landscapes in which clinical departments run separate systems with heterogeneous data formats and no centralization. Because of this, hospitals possess a "large but unstructured data treasure" that cannot currently be used for advanced analytics or simulation. To overcome this, hospitals are now building foundational infrastructures such as Clinical Data Repositories (CDRs) to centralize structured patient data for secondary use. He emphasized that Digital Twins can only create value once data harmonization, interoperability, and standardized documentation practices are established.

2. Organizational & Governance Factors

E06 underlined that the most crucial prerequisite for digital transformation is early and explicit support from the hospital board. Large-scale digital innovations require clear mandates, sufficient budgets, project governance, and active involvement from all major stakeholders, including physicians, nursing staff, administration, IT, and facility management. Unstructured legacy processes, unclear responsibilities, and silo thinking make implementation extremely challenging. He emphasized that Digital Twins represent enterprise-wide transformation, not isolated IT tools, requiring strong project management, cross-departmental coordination, and robust communication structures. He also highlighted the necessity of iterative pilot phases and "quick wins" to build trust and momentum.

3. Individual & Cultural Aspects

E06 described hospital staff attitudes toward digital technologies as highly heterogeneous. Younger clinicians tend to be open and digitally competent, while older generations require more support, clearer benefit communication, and training formats that fit their routines. Trust plays a central role: staff worry about data accuracy, system reliability, and usability, particularly when technologies appear overly complex (e.g., VR planning tools).

He stressed that successful adoption depends on practical relevance, reduction of perceived burden, and solutions that integrate seamlessly into existing workflows. Change management was described as an organizational weakness in hospitals and an area requiring substantial improvement.

4. Environmental & Regulatory Conditions

E06 described data protection as strict but necessary, given the sensitivity of medical and Digital-Twin-level data. He warned that Digital Twins create “ultra-sensitive” representations of individual patients, amplifying the consequences of any data leak. He noted that regulatory landscapes vary across German states, with some, including his own, enforcing particularly stringent interpretations of GDPR. He highlighted the importance of detailed risk analyses, contractual safeguards, data-processing agreements, and choosing infrastructure providers that avoid problematic third-country access. Regarding incentives, he acknowledged that regulations such as KHZG can accelerate digital transformation because “penalties make hospitals act,” even if ideally hospitals would innovate out of intrinsic motivation.

5. Strategic Perspective & Future Outlook

E06 sees Digital Twin adoption following a multi-stage trajectory. Over the next 3–5 years, he expects hospitals to engage mainly in proof-of-concept projects tied to specific use cases. Real operational deployment will likely occur after five years, once data foundations, harmonized infrastructures, and organizational prerequisites are in place. He emphasized that there will not be a single monolithic Digital Twin, but rather multiple use-case-specific twins in areas such as process optimization, OR planning, clinical decision support, and facility management. He expects long-term convergence with AI-based decision support systems, but only after visual realism, workflow integration, and data structures have matured.

Important Quotes

- “We have a huge data treasure, but it is not centralized and not structured, hospitals are not yet at the level required to build a real, value-creating Digital Twin.”
- “The most important thing is the backing of the board; without a clear mandate, budget, and project governance, nothing moves forward in a hospital.”
- Individual & Cultural Aspects
- “Younger generations are very open, but older generations must be picked up, they know their processes, but you must show them the benefit.”
- Environmental & Regulatory Conditions
- “Digital Twin data would be ultra-sensitive; the regulation is necessary, but we have to find a balance between security and innovation.”
- “It will not be one single Digital Twin, there will be different use cases, and only in five-plus years will we see realistic implementation.”

Appendix B.7 Expert Interview Summary E07 (Academic Researcher)

1. Technological & System Readiness

Expert E07 assessed Digital Twin maturity in healthcare as very low, rating the current level as "3 out of 10." He emphasized that while biomedical research already produces high-resolution models for specific organs or cellular components, these are not yet robust enough for clinical decision-making. At the system level, he noted substantial gaps in real-time data availability. Most hospitals lack the ability to create full, continuously updated data replicas, making it impossible to build dynamic Digital Twins that reflect current reality rather than outdated snapshots. Even institutions developing data repositories face delays, partial replication, and limited granularity. He concluded that without real-time data infrastructures, Digital Twins cannot progress beyond isolated research experiments.

2. Organizational & Managerial Capabilities

E07 highlighted that hospitals must separate operational IT from innovation-oriented digital teams. Daily system maintenance and troubleshooting require different capabilities than building simulated environments or modelling operating rooms. These teams must collaborate closely so that Digital Twin developers understand the logic, limitations, and semantics of the data used. He emphasized that healthcare environments are inherently non-standardized, unlike factories or engineered environments, making modelling complex and highly dependent on clinical knowledge. He argued that Digital Twins require strong interdisciplinary coordination, deep understanding of real-world workflows, and awareness of the "messy" nature of hospitals, patients, and clinical processes.

3. Environmental, Regulatory & Policy Factors

E07 described the European regulatory landscape as strong in writing regulations but weak in implementation capacity. He noted the EU's tendency to pioneer frameworks such as the AI Act but warned that regulators themselves often lack sufficient technical understanding to enforce them effectively. He stressed the need for capacity building for regulators and for the organizations being regulated. He also emphasized that regulation of Digital Twins implicitly regulates multiple adjacent domains: data quality, semantics, interoperability, metadata cataloguing, whether intended or not. He sees the European Health Data Space as a positive step, although its current granularity levels are insufficient for advanced Digital Twin use cases.

4. Strategic, Value & System-Level Perspectives

E07 highlighted the **long-term value** of Digital Twins in enabling evidence-based decision-making for managers and policymakers. He argued that Digital Twins could enable simulation of alternative scenarios: testing hospital layouts, resource allocations, or policy changes before implementation. He noted parallels with medical simulation and education, which already use digital training environments to improve practical decision-making. In his view, Digital Twins are most valuable when they meaningfully increase the quality of decisions rather than when they serve as visually appealing but strategically hollow representations.

5. Future Outlook, Culture & Critical Reflection

E07 cautioned that Digital Twins are currently viewed by many hospital leaders as a "nice-to-have" or PR tool, not a serious instrument for improving service delivery.

He believes small clinical models (e.g., disease-specific simulations) will appear before full institutional twins. He also stressed the risk of oversimplification: copying the aesthetics of industrial Digital Twins may produce attractive visualizations but fail to improve real-world decisions. He stated that true usefulness will depend on data richness, realistic modelling of human and biological variability, and the evolution of leadership mindsets. He expects hospitals to adopt Digital Twins only gradually, once measurable, decision-improving use cases emerge.

Important Quotes

- “From one to ten, I would say three. They are still pretty much immature, because real maturity is when you can actually use it for decision making.”
- “One critical thing is to separate the IT department into operational teams and those that actually work on replicating the environment, but these teams must communicate.”
- “The EU has done a good job inventing regulation, but I’m not sure it will be able to do a good job implementing the regulation it invented.”
- “The biggest long-term value of digital twins is decision-making simulation, moving from non-evidence-based policy to simulated, evidence-based decisions.”
- “For now it is a nice-to-have. Many people see a 3D copy of their building as PR, something that looks modern but does not really improve service delivery.”

Appendix B.8 Expert Interview Summary E08 (MedTech Professional)

1. Market Understanding & Digital Twin Relevance

Expert E08 emphasized that radiology is the most digitally advanced field in medicine, driven by the historical need to digitize imaging workflows early. Compared globally, the United States leads in radiology AI adoption due to faster FDA approvals, with Europe and especially Germany lagging behind because of limited digital maturity and legacy systems. She highlighted two major trends shaping the market: AI-based image analysis and ambient scribing solutions that automatically generate clinical documentation. Radiology workflows already include simulation-like elements, which she sees as conceptually close to Digital Twin principles. AI-driven triage, live 3D imaging, and motion-based visual diagnostics are accelerating, making the field particularly receptive to Digital Twin–related innovation.

2. Implementation Requirements & Adoption Barriers

E08 stressed two critical dimensions: (1) technical prerequisites, including interoperability standards such as HL7 and FHIR, and (2) organizational readiness, especially openness to change. She described radiology as an environment where clinicians work at extreme speed and in highly repetitive routines. Because radiologists think “in seconds and clicks,” adoption barriers are high: any new system that slows them down, even slightly, faces resistance. Many European hospitals use decades-old RIS/PACS systems, making integration complex and limiting innovation speed. She highlighted that end-user trust is fragile; clinicians rapidly lose confidence in AI tools if a model produces even a single error.

3. Partnerships & Collaboration with Hospitals

E08 explained that successful collaboration requires deep alignment with hospital workflows and user needs. Jacobian works closely with radiologists, IT departments, CIOs/CTOs, and radiology chains, adapting messages to each stakeholder group. The company maintains direct sales channels and indirect channels via major OEM partners such as Siemens Healthineers and GE, where Jacobian solutions are embedded into PACS ecosystems. She stressed that clinical co-development, pilot projects, and long-term onboarding support are essential, because hospitals expect stability, reliability, and tailored workflows rather than generic digital solutions. Trust-building and continuous feedback loops are central to long-term adoption.

4. Value Creation & Business Models

She highlighted efficiency and productivity as the dominant value drivers in radiology. Time savings of even a few seconds per case represent substantial financial and operational impact. AI-based workflow optimization therefore resonates strongly with hospital leadership. Business models vary by region: in the U.S., large radiology chains focus on speed and throughput, whereas European hospitals rely on long-term contracts and demonstrate lower innovation velocity. Jacobian's value proposition centers on automated, standardized reporting that reduces cognitive load, minimizes errors, and ensures compliance with clinical guidelines. She noted that quality assurance and standardization are economically relevant because radiology reports shape downstream clinical decisions across the entire patient journey.

5. Regulatory Environment & Strategic Outlook

E08 described regulation as a major bottleneck, particularly for products approaching the threshold of becoming medical devices. The FDA is comparatively permissive, but European frameworks impose stricter requirements. She highlighted a recent case where Jacobian had to redesign a product entirely because regulators deemed the automated report summary "too close to clinical decision-making." She emphasized that regulatory compliance is essential but slows innovation. Looking ahead 5–10 years, she expects the radiology market to consolidate around integrated workflow ecosystems that combine scheduling, imaging, reporting, and analytics, a structure that will naturally support Digital Twin–like simulation. She stressed that the biggest long-term opportunity lies in unifying fragmented systems and eliminating silos.

Important Quotes

- "Radiology is absolutely the field that is furthest ahead in digitalisation, the number one driver of FDA-approved AI solutions."
- "Radiologists think in seconds and clicks, if a system slows them down even slightly, it won't be used."
- "We work differently with CIOs, IT departments, and clinicians, every group needs a different message and different benefits."
- "Productivity is the number one driver, time savings of even a few seconds per day make a huge difference in radiology."
- "Regulation is a massive bottleneck; we had to change an entire product because it crossed the fine line to becoming a medical device."

Appendix B.9 Expert Interview Summary E09 (Physician)

1. Perception & Usefulness

Expert E09 described Digital Twin concepts as already partially embedded in cardiology workflows, even if they are not labeled that way. She emphasized that CT- and MRI-based 3D reconstructions, valve simulations, flow analyses, and stent-planning tools function as “early Digital Twin–like systems.” She sees the greatest value in pre-procedural simulation, allowing clinicians to rehearse complex interventions and assess different device types, access routes, and risk scenarios. She also identified strong potential in long-term prediction, such as modelling cardiac remodeling under specific treatments. For her, the primary benefit is planning certainty, which reduces stress for physicians, teams, and patients.

2. Everyday Integration

E09 stated that Digital Twin tools must be radically simple to integrate into cardiology practice. They should be embedded directly into existing clinical software and accessible at the point of care without additional steps, rooms, or systems. She highlighted time pressure as the primary barrier: clinicians have no spare capacity to explore complex tools. Trust is another central condition; she requires transparency about how recommendations are generated. Early AI tools she has used (e.g., automatic segmentation, valve-size suggestions, risk prediction) were helpful but often immature. For daily use, she prefers visual, intuitive 3D feedback rather than numeric tables or abstract outputs.

3. Collaboration & Environment

E09 stressed that successful adoption requires broad interdisciplinary involvement, including physicians, nursing staff, cath-lab teams, IT, administration, and critically, hospital leadership. She prefers short, case-based training embedded directly into clinical work, as long-format workshops are impractical. She identified finance, infrastructure, and cultural attitudes as major environmental factors. Many hospitals lack modern IT foundations, and clinicians often hesitate to adopt systems whose mechanisms they do not fully understand. She also pointed to systemic inertia and unclear responsibilities (e.g., data maintenance, liability) as barriers that slow implementation.

4. Organizational & Managerial View

E09 emphasized that Digital Twin adoption depends entirely on leadership support. Without executive commitment, no funding, resources, or operational adjustments can occur. She described herself as actively championing digital tools but noted that higher management often lacks digital literacy or capacity. She desires a clear digital strategy, reliable long-term budgets, and reduced bureaucratic hurdles. Professional societies, in her view, could accelerate adoption by providing guidance, certification standards, and training formats that increase clinician confidence and signal legitimacy to the field.

5. Personal Perspective & Outlook

E09 envisions an “ideal Digital Twin” as a patient-specific, realistic, learning system that integrates multimodal data (imaging, labs, ECGs) and provides early warnings or treatment-effect predictions.

She would use such a system regularly if it were easy to operate, seamlessly integrated into her workflow, and demonstrated clear clinical benefits in decision-making and patient outcomes. She believes Digital Twins will become relevant but expects a multi-year adoption window due to infrastructural deficits, limited time capacities, and cultural hesitation within hospitals.

Important Quotes

- “We already work with something like that: 3D heart models from CT or MRI feel very much like a digital twin, even if we don’t call them that.”
- “It has to be simple. I have no time to click through five menus; it must be where I already work.”
- “Without the infrastructure and without the right mindset, none of this will arrive in everyday clinical practice.”
- “If the hospital leadership is not convinced, nothing happens – absolutely nothing.”
- “If it’s easy to use and really improves my decisions and my patients’ outcomes, I would use it immediately.”

Appendix B.10 Expert Interview Summary E10 (Consultant)

1. Market and Technology Perception

Expert E10 described the maturity of Digital Twin technologies in German hospitals as very low and largely confined to radiology, where 3D imaging, segmentation, and simulation workflows have already been established. Outside radiology, she sees only scattered explorations with a strong research character. She emphasized that international markets, particularly the U.S, are significantly more advanced, while German hospitals remain cautious and often lack the digital foundation required. She argued that patient-generated data and wearable streams function as “mini-twins,” showing how consumers already engage with personalized digital monitoring while hospitals trail behind. Overall, she sees conceptual openness but very limited operational readiness.

2. Organizational and Implementation Factors

E10 stressed that successful Digital Twin implementation depends primarily on leadership direction, clear use-case definition, and clinician openness. Many hospitals suffer from silo structures, fragmented responsibilities, and highly outdated hardware that cannot support advanced simulations. She noted that physicians often lack time or incentives to engage with innovation initiatives, especially when daily operations dominate their capacity. Hospitals frequently underestimate the need for structured change management, interdisciplinary coordination, and the alignment of IT, clinicians, and administration. She highlighted that internal readiness varies widely and that user trust and transparency must be actively built.

3. Strategic and Economic Logic / Value Creation

E10 emphasized that Digital Twins create value primarily in high-volume, highly specialized hospitals, where repetitive workflows and substantial case numbers justify the investment. She linked Digital Twins to personalized and individualized medicine, arguing that they offer strong strategic positioning benefits for hospitals that want to differentiate through innovation.

However, she highlighted that Germany's reimbursement structures offer few incentives for hospitals to adopt advanced digital technologies, resulting in "innovation only where financing is available," such as university hospitals or research partnerships. Economic viability therefore depends on scale, funding mechanisms, and the ability to translate predictive insights into operational efficiency.

4. Regulatory and External Environment

E10 described MDR and GDPR requirements as major barriers for MedTech and hospital innovation, particularly for tools crossing the threshold toward medical-device classification. She stressed the importance of explainable AI, noting that clinicians need to understand how outputs are generated to use them responsibly. She argued that German institutions frequently cite data protection as a blanket argument against innovation, even in scenarios where patient consent would legally enable data use. Compared internationally, she sees Germany adopting a regulation-first rather than innovation-first approach. External funding programs such as the Innovation Fund help compensate for this and can accelerate pilot projects.

5. Managerial and Strategic Perspective

E10 expects Digital Twins to be adopted selectively, not universally. She anticipates their use primarily in leading centers of excellence with strong clinical specialization, large case volumes, and reputational ambitions. She sees strategic value in Digital Twins for attracting talent, conducting research, and building hospital branding. Long term, she anticipates a gradual rise in adoption over the next 10–15 years, driven by generational shifts among clinicians and the increasing dominance of AI-supported decision-making. She emphasized that without sustained leadership commitment and strategic prioritization, Digital Twins will remain isolated flagship projects rather than system-wide solutions.

Important Quotes

- "I have seen relatively little that hospitals actually use, the biggest use case is radiology."
- "The hardware is often so outdated; you can have a cool Digital Twin, but the hospital simply cannot provide what is needed."
- "This is a huge opportunity for personalized and individualized medicine."
- "For many manufacturers it is extremely difficult to get certification as a medical device."
- "It will not be nationwide, rather specialized hospitals that are simply top in their indication."

Appendix B.11 Expert Interview Summary E11 (MedTech Professional)

1. Market Understanding & Digital Twin Relevance

Expert E11 described her company's neurosurgery and radiosurgery software ecosystems as mature Digital Twin–like systems, even though the term "Digital Twin" is rarely used in practice. She explained that her company has been building high-precision anatomical patient models for decades, combining multimodal imaging (MRI, CT, tractography) into detailed digital replicas of patients' brains and tumors. These models enable individualized surgical planning, intraoperative navigation, and dose-planning in radiotherapy.

She emphasized that such tools already constitute “true digital replicas” of patient anatomy, supporting prediction, risk assessment, and iterative treatment planning.

Across the market, she sees AI-supported segmentation, image fusion, and holographic visualization becoming standard, with Digital Twin capabilities increasingly embedded rather than explicitly marketed.

2. Implementation Requirements & Adoption Barriers

E11 highlighted hospital IT and data infrastructure as the most significant barrier. The systems must integrate with PACS and run within hospital servers, which are often outdated, underfunded, or lack space and security capacity. She described hospitals’ skepticism toward cloud services, which slows adoption and limits product flexibility. Technical integration requires long onboarding cycles, IT approvals, and manual software updates that still require technicians onsite. She also stressed the challenge of obtaining sufficient, diverse, high-quality patient data to train and validate AI-enhanced solutions, noting that regulatory constraints and missing metadata often restrict what is available. Beyond infrastructure, she highlighted openness, training, and culture as critical adoption prerequisites, with radiotherapy technicians and neurosurgeons requiring extensive onboarding to use advanced planning tools safely.

3. Partnerships & Collaboration with Hospitals

E11 described her company model as one of deep clinical integration, working closely with university hospitals, radiosurgery centers, medical physicists, and key opinion leaders. Collaboration is strongest in high-complexity fields where clinicians actively co-develop new features and provide feedback that flows directly into product releases. She noted that medical leadership, particularly chief physicians, play an outsized role in purchasing and adoption decisions, often shaping procurement processes and determining which technologies become the standard of care. She emphasized that trust in the brand, robust clinical evidence, and long-term relationships are essential. Start-ups face high barriers due to lacking reputation, complex integrations, and demanding validation standards.

4. Value Creation & Business Models

E11 stated that her companies value proposition lies in precision, safety, and individualized treatment, especially for tumors and complex neurosurgical procedures. Digital Twin–like planning tools reduce uncertainty, support outcome predictions, and enable tailored dose planning or surgical trajectories. She described these tools as strategically important for hospitals seeking reputation, talent attraction, and research leadership, particularly in high-volume centers. From a business perspective, value creation depends on clinical relevance and reimbursement. Procedures tied to coding or reimbursement incentives see much stronger adoption, especially in the U.S., where reimbursement can even drive the use of technologies that clinicians consider only marginally beneficial. For Germany and Europe, she highlighted limited reimbursement as a barrier but noted strong traction in university clinics due to research funding and more innovation-oriented cultures.

5. Regulatory Environment & Strategic Outlook

E11 highlighted MDR, FDA requirements, and global data-transfer rules as key brakes on innovation speed. AI-enhanced products require multiple datasets for training, validation, and regulatory evaluation, and assembling these datasets is increasingly difficult due to national data-protection rules and missing metadata.

She gave examples of international collaborations delayed by year-long negotiations over data-transfer safeguards. Regulatory uncertainty shapes her companies innovation strategy: teams hesitate to pursue novel concepts if approval is unlikely.

Looking ahead, she expects Digital Twin–related features to accelerate because AI, segmentation, fusion, and holographic visualization are becoming baseline expectations. She believes the strongest developments will occur in university hospitals and specialized centers, while adoption in general hospitals will remain slow due to infrastructure and regulatory constraints.

Important Quotes

- "We basically already have a digital version of the patient's brain, that is, in my view, already a digital twin."
- "The hospital IT is one of the biggest challenges, the systems are outdated, and the servers can't always support what we need."
- "The chief physicians make the purchase decisions; they have enormous influence, especially because they shape the research and attract talent."
- "This is a huge step for individualized treatment, planning based on the patient's own data makes an enormous difference."
- "The approval process is incredibly complicated and slows down innovation, sometimes we don't pursue ideas because we fear they won't get approved."

Appendix B.12 Expert Interview Summary E12 (Academic Researcher)

1. Technological & System Readiness

Expert E12 assessed the technological maturity for Digital Twin applications in hospitals in Germany, Austria, and Switzerland as extremely low. He stressed that hospitals lack the digital foundations necessary for real-time, data-driven simulation, particularly structured data, semantic annotation, and interoperable documentation. In his view, Digital Twins are mainly a buzzword applied to long-existing methods such as rule-based algorithms or predictive analytics. He argued that the gap between the hype and practical digitalisation is vast: many hospitals still rely on faxing, PDFs, and unstructured notes, which fundamentally limits the feasibility of any advanced modelling. He confirmed that Digital Twins can only be as good as the data feeding them, and current data maturity is far from sufficient.

2. Organizational & Managerial Capabilities

E12 identified poor documentation culture, fragmented data structures, and historical silo systems as major obstacles to digital innovation. He emphasized that hospitals must shift from free-text documentation toward structured, coded data (e.g., ICD-10, OPS, SNOMED CT) to enable any advanced analytics or simulation. He underscored that change will be painful, as clinicians often resist altering documentation habits. He also highlighted the importance of strong process understanding and cross-functional collaboration between IT, clinicians, and management, but noted that many hospitals lack the internal capacity to challenge legacy workflows or push structural digital reform.

3. Environmental, Regulatory & Policy Factors

E12 argued that regulatory frameworks pose necessary but substantial barriers to innovation.

While GDPR is often misinterpreted and used as a blanket argument against data sharing, he sees the Medical Device Regulation (MDR) as the far stronger obstacle, leading to high compliance costs and forcing many MedTech companies to withdraw products from the market. He warned that MDR requirements overshoot their goal, harming treatment quality by removing clinically proven tools that cannot be affordably recertified. He stressed that all regulatory environments in Europe pursue single-objective logic (e.g., only privacy, only device safety), neglecting broader goals such as treatment quality, innovation speed, and patient outcomes. This imbalance, he argued, risks slowing or even reversing digital progress.

4. Strategic, Value & System-Level Perspectives

E12 sees value in Digital Twin concepts in principle, especially when large volumes of structured data enable prediction, simulation, and improved decision-making. He believes data-driven forecasting would benefit both operational hospital management and patient care, provided the underlying data quality improves. However, he argued that before pursuing advanced technologies, hospitals must address fundamental digital deficits and "do their homework." He described the broader system as severely underfunded, with hospital IT budgets far below international standards, making it unrealistic to expect large-scale innovation. He highlighted that innovation is structurally hindered: without proper funding, staffing, and maintenance strategies, even appropriately designed digital tools cannot scale.

5. Future Outlook, Culture & Critical Reflection

E12 expects gradual improvement due to generational shifts among clinicians and increased familiarity with AI systems in daily life. He compared the acceptance curve of future clinical algorithms to the adoption of ChatGPT: initial skepticism gives way to trust once usefulness is demonstrated. He believes the "Quantified Self" movement and widespread use of wearables will improve personal health data and foster a new cultural openness toward digital health concepts. At the same time, he warned that overreliance on poorly documented or unstructured data will prevent any meaningful Digital Twin development. He also emphasized that misguided interpretations of data protection can harm patient safety, for example, when critical allergy or medication information is hidden due to excessive caution. Overall, he sees Digital Twin research evolving faster than clinical reality, with hospitals trailing far behind due to structural, cultural, and regulatory inertia.

Important Quotes

- "The maturity is a catastrophe: hospitals still fax and work with PDFs; that has nothing to do with a digital twin."
- "You must collect good, structured data; a PDF file is worthless for IT, you can't do anything with it."
- "The MDR shoots far beyond its goal; companies go bankrupt because recertification is so expensive."
- "Hospitals spend one-and-a-half to two percent on IT, with that you cannot expect crazy innovative things to happen."
- "Misunderstood data protection can lead to people dying, if information is hidden in an emergency, that is the consequence."

Appendix C – Qualitative Coding Framework

Appendix C.1 Expert Interview Coding Guideline

1. Technological Factors (TAM, TOE)

Category	Subcategory	Definition	Anchor Example	Coding Rule (Use when...)	Exclusion Role (Use not when...)
A -Technological	**A1 - Percieved Usefulness**	Statements referring to the perceived usefulness or expected benefits of Digital Twins	"Digital twins would let me rehearse complex procedures beforehand." (E10)	When benefits or improvements due to DTs are mentioned	If usefulness is not related to DTs
	A2 – Ease of Use / Complexity	Statements regarding user-friendliness or perceived complexity	"Every extra click kills adoption, it must run directly in my workflow." (E08)	When ease of use or complexity is discussed	When the barrier is organizational
	A3 – Data Quality & Interoperability	Statements about data availability, quality, integration, standards	"Our data is in silos and mostly unstructured, impossible for real twins." (E01)	When data or interoperability is cited as a factor	When skills or staffing is the main issue
	A4 – Technical Maturity	Statements about maturity, stability, reliability of DT technologies	"Outside radiosurgery, twins are still experimental, we're far from real-time." (E12)	When readiness level is discussed	When workflow challenges dominate
	A5 – Infrastructure Requirements	Structural or IT infrastructure needs	"We simply don't have the computing power for real-time simulations." (E06)	When hardware/software limitations are mentioned	When human skills or workflows are the issue

2. Organizational Factors (TOE)

Category	Subcategory	Definition	Anchor Example	Coding Rule (Use when...)	Exclusion Role (Use not when...)
B – Organizational	**B1 – Resource Availability**	Availability of financial, human, or time resources	"We don't have staff to operate additional digital systems." (E10)	When resources are insufficient	When knowledge gaps dominate (→ B2)
	B2 – IT Capabilities & Skills	Skills, competencies, technical know-how	"Clinicians don't know how to work with simulation models." (E05)	When skills or competencies are the issue	When infrastructure is lacking
	B3 – Workflow Integration	Fit into existing processes and routines	"Switching systems slows everything down, integration is essential." (E08)	When integration into routines is discussed	When general attitudes are the focus
	B4 – Leadership Support	Managerial support, sponsorship, prioritization	"If the board doesn't support it, nothing happens, it dies immediately." (E02)	When top-down support is referenced	When resistance is individual
	B5 – Governance & Decision Structures	Internal rules, decision-making, approval processes	"Procurement delays everything, innovative tools get stuck for months." (E11)	When internal governance shapes adoption	When barriers are external (→ C)

3. Environmental Factors (TOE)

Category	Subcategory	Definition	Anchor Example	Coding Rule (Use when...)	Exclusion Role (Use not when...)
C – Environmental	**C1 – Regulation & Data Protection**	Regulatory constraints, data security, compliance	"MDR is the real blocker, products even disappear from the market." (E12)	When regulations hinder or enable adoption	When internal governance is meant
	C2 – Market Pressure / Competition	Competition, market expectations, industry pressure	"Competitors already use advanced simulation tools, hospitals must keep up." (E07)	When adoption is influenced externally	When internal pressure is meant
	C3 – Vendor Ecosystems & Partnerships	Influence of vendors, collaborations, ecosystems	"Siemens drives adoption simply because hospitals trust them." (E04)	When external actors shape adoption	When internal IT issues dominate
	C4 – Reimbursement & Funding Models	Payment structures, incentives, ROI	"If there's no reimbursement code, hospitals simply won't use it." (E03)	When funding logic matters	When general resource shortages dominate

4. Individual Factors

Category	Subcategory	Definition	Anchor Example	Coding Rule (Use when...)	Exclusion Role (Use not when...)
D – Individual	**D1 – Trust / Acceptance**	Trust, confidence, skepticism toward DTs	"I won't rely on a system if I don't know how it makes decisions." (E10)	When personal trust or skepticism is shown	When regulations cause risk
	D2 – Perceived Risk	Liability, safety concerns, emotional risk perception	"If the twin is wrong, we are liable, that's a huge risk." (E05)	When perceived risk is expressed	When technical maturity is meant
	D3 – Attitudes Toward Innovation	Openness to new technologies	"Clinicians are conservative, adoption takes years." (E04)	When innovation readiness is discussed	When workflow issues dominate
	D4 – Experience & Skills	Personal skills, training, expertise	"Engineers understand twins, clinicians don't, huge expertise gap." (E12)	When individual competence is at issue	When resource constraints dominate

5. Managerial & Strategic Factors

Category	Subcategory	Definition	Anchor Example	Coding Rule (Use when...)	Exclusion Role (Use not when...)
E – Managerial	**E1 – Dynamic Capabilities**	Sensing, seizing, transforming capabilities	"Hospitals struggle to scale digital innovations they lack transformation skills." (E01)	When strategic abilities are mentioned	When technical skills are meant
	E2 – Resource Orchestration	Ability to combine and align resources	"Teams work in silos, coordination is too weak for complex systems." (E07)	When orchestration of resources is discussed	When resource *availability* is meant (→ B1)
	E3 – Strategic Fit / Value Logic (VBHC)	Alignment with long-term value creation	"Twins fit our shift toward outcome-based care, long-term it makes sense." (E08)	When strategic alignment is referenced	When tactical issues dominate
	E4 – Long-term Strategy & Vision	Future outlook, investment logic	"Hospitals must first fix basics, twins only make sense later." (E12)	When long-term strategy is mentioned	When daily operations are discussed

6. Value Creation & Use Cases

Category	Subcategory	Definition	Anchor Example	Coding Rule (Use when...)	Exclusion Role (Use not when...)
F – Value	**F1 – Clinical Value**	Benefits for patient outcomes, safety	"Twins reduce surgical complications, that's the biggest benefit." (E09)	When clinical outcomes improve	When operational efficiency is meant
	F2 – Operational Value	Efficiency, process optimization	"Twins could reduce bottlenecks in the OR, huge efficiency potential." (E07)	When processes are improved	When clinical value is meant
	F3 – Commercial Value	Economic or marketing value	"Hospitals can differentiate themselves with advanced simulation tech." (E11)	When commercial aspects are referenced	When clinical or operational value dominates

Appendix C.2 Category Frequencies & Expert Coverage

Category	Subcategory	X/12	Interviewees	Expertgroup
A -Technological	A1 - Percieved Usefulness	7	E03,E04,E05,E08,E09,E10,E11	Consultants, Physicians, MedTech
	A2 – Ease of Use / Complexity	6	E02,E03,E05,E06,E08,E09	MedTech, Consultants, Physicians, Hospital Manager
	A3 – Data Quality & Interoperability	10	E01,E02,E04, E05,E06,E07,E08,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	A4 – Technical Maturity	11	E02,E03,E04;E05,E06,E07,E08,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	A5 – Infrastructure Requirements	10	E01,E02,E05,E06,E07,E08,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
B – Organizational	B1 – Resource Availability	11	E01,E02,E03,E04,E05,E06,E07,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	B2 – IT Capabilities & Skills	5	E02,E05,E09,E11,E12	MedTech, Physicians, Researchers
	B3 – Workflow Integration	9	E01,E02,E04,E05,E06,E08,E09,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	B4 – Leadership Support	8	E01,E02,E03,E04,E05,E06,E07,E09	Consultant, MedTech, Physician, Hospital Manager, Researcher
	B5 – Governance & Decision Structures	9	E01,E02,E04,E06,E07,E08,E09,E10,E11	Consultant, MedTech, Physician, Hospital Manager, Researcher
C – Environmental	C1 – Regulation & Data Protection	12	E01,E02,E03,E04,E05,E06,E07,E08,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	C2 – Market Pressure / Competition	8	E01,E02,E03,E04,E07,E08,E10,E11	MedTech, Consultants, Researchers
	C3 – Vendor Ecosystems & Partnerships	1	E06	Hospital Manager
	C4 – Reimbursement & Funding Models	9	E01,E02,E03,E04,E05,E09,E10,E11,E12	Consultants, MedTech, Physicians, Researchers
D – Individual	D1 – Trust / Acceptance	11	E01,E02,E03,E04,E05,E06,E08,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	D2 – Perceived Risk	2	E02,E03	MedTech, Consultant
	D3 – Attitudes Toward Innovation	10	E03,E04,E05,E06,E07,E08,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	D4 – Experience & Skills	0		
E – Managerial	E1 – Dynamic Capabilities	4	E01,E02,E07,E12	Consultant, MedTech, Researchers
	E2 – Resource Orchestration	9	E01,E03,E04,E05,E06,E07,E08,E10,E11	Consultant, MedTech, Physician, Hospital Manager, Researcher
	E3 – Strategic Fit / Value Logic	7	E02,E03,E06,E07,E10,E11,E12	MedTech, Consultants, Hospital Manager, Researchers
	E4 – Long-term Strategy & Vision	7	E01,E02,E03,E05,E06,E09,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
F – Value	F1 – Clinical Value	12	E01,E02,E03,E04,E05,E06,E07,E08,E09,E10,E11,E12	Consultant, MedTech, Physician, Hospital Manager, Researcher
	F2 – Operational Value	8	E01,E02,E03,E04,E06,E07,E08,E11	Consultant, MedTech, Hospital Manager, Researcher
	F3 – Commercial Value	10	E01,E02,E03,E04,E05,E06,E07,E08,E10,E11	Consultant, MedTech, Physician, Hospital Manager, Researcher

Meta Pattern:	#1 Data Quality (A3) + Infrastructure (A5) + Regulation (C1)	#2 Workflow Integration (B3) + Ease of Use (A2) + Trust (D1)	#3 Strategic Fit (E3) + Leadership Support (B4) + Resource Availability (B1)	#4 Commercial Value (F3) + Clinical Value (F1) + Operational Value (F2)	#5 Market Pressure (C2) + Competitive Positioning (B5/E2) + Innovation Incentives (C4/F4)	#6 Regulation (C1) + Reimbursement (C4) + Approval Complexity (F4)	#7 Resource Orchestration (E2) + Multi-stakeholder Alignment (B3/B5) + Role Clarity (C3)	#8 Technical Maturity (A4) + Long-Term Vision (E4) + Dynamic Capabilities (E1)	#9 User Skills (B2) + Attitudes toward Innovation (D3) + Generational Differences	#10 Domain-Specific Readiness (A2/A4/F1/F2/F3)
Core Mechanism	Digital Twins cannot scale because hospitals lack structured, interoperable data (A3), run on outdated legacy systems (A5), and face compliance-first interpretations of data protection (C1).	Clinicians adopt Digital Twin–like systems only if the tools fit seamlessly into existing workflows (B3), require few clicks and low cognitive load (A2), and present outputs that are explainable (D1).	Successful adoption depends on whether leadership prioritises Digital Twins strategically (E3), allocates dedicated resources/personnel (B1), and builds governance structures for long-term scaling (B4).	Interviews consistently show that adoption requires clear clinical relevance (F1), measurable efficiency gains (F2), and a compelling economic justification (F3).	Specialties facing competitive pressure (radiology, oncology, cardiology) adopt faster. Market maturity and reimbursement (C4, F4) influence incentives and speed.	Regulatory burdens (MDR, GDPR) interact with reimbursement uncertainty (C4) and complex approval pathways (F4) to slow down AI-heavy Digital Twin solutions.	Cross-functional alignment, physicians, IT, nursing, management, vendors, is essential but often missing. Role ambiguity slows digital projects.	Hospitals misinterpret early-stage Digital Twins as "not ready," while experts describe innovation as iterative and requiring long-term capability development.	Digital adoption varies greatly by skills (B2) and individual openness (D3). Younger clinicians are more receptive; older staff are skeptical or overwhelmed.	High-tech specialties (radiology, neurosurgery, cardiology) already use Digital Twin–adjacent systems. Administrative and general wards lag far behind.
Interpretation	This is the single strongest meta-pattern: poor data foundations coupled with strict GDPR/MDR create structural barriers long before DT-specific issues arise.	This pattern explains adoption at the point of care: if the tool breaks the workflow or feels like a black box, trust collapses immediately.	This pattern highlights that DTs are management and transformation projects, not IT tools. Leadership literacy is a decisive factor.	This is the core value logic driving investment decisions: DTs are adopted where benefit > cost > workflow disruption.	Adoption is accelerated in market-driven, volume-driven, or high-innovation environments.	This is the primary barrier for MedTech vendors and explains stagnation in Europe compared to the US.	This pattern reflects the organizational complexity of hospitals and the need for interdisciplinary governance.	Digital Twins require multi-year evolution, but hospitals expect ready-made tools, creating an expectation gap.	This explains heterogeneity within specialties and why transformation is uneven inside each hospital.	Digital Twin maturity is highly uneven, with islands of excellence and vast areas of low readiness.
Observed across	E01, E02, E03, E04, E06, E07, E08, E10, E12	E03, E04, E05, E07, E08, E09, E11	E01, E03, E04, E06, E07, E09, E10, E12	every interview with physicians & MedTech (E05–E11), consultants (E01–E04, E10), research (E07, E12)	E01, E03, E05, E07, E08, E10, E11	E02, E06, E07, E08, E10, E11, E12	E02, E03, E04, E05, E06, E08, E09, E10	E03, E04, E06, E07, E09, E10, E12	E04, E05, E06, E07, E08, E09	E05 (trauma), E08 (radiology), E09 (cardiology), E11 (neurosurgery/radiosurgery), E04/E10 (hospital mgmt)

Appendix D: Survey Questions Outline

Q No.	Question	Question Type	Answer Options
Block 1: Healthcare Experience			
1	Have you ever received medical care from a doctor or hospital (e.g. for checkups, illness, injury or treatment)?	Multiple choice	Yes, No
2	Have you ever undergone major surgery or long-term medical treatment?	Multiple choice	Yes, No, Prefer not to say
3	Do you have a chronic health condition that requires ongoing monitoring treatment?	Multiple choice	Yes, No, Prefer not to say
4	Do you currently use any digital health tools such as wearables, fitness trackers, or health apps (e.g. Fitbit, Apple Watch, Garmin, Oura, blood pressure apps)?	Multiple choice	Yes regularly, Yes occasionally, No
Block 2: Patient Digital Twin Scenario			
Scenario: *You injure your hand, and it turns out to be a fracture. You go to the hospital, and doctors take detailed scans of your bones. This data is used to create a digital replica of your hand – a "Digital Twin". With this virtual model, they can test different treatment options and choose the best for you.*			
5	Before this survey, had you heard of the idea of a "Digital Twin" in healthcare?	Multiple choice	Yes, No
6	Do you believe that using a Digital Twin of a patient, like in the example above, could improve healthcare outcomes?	5-point Likert scale	Strongly agree, somewhat agree, neither agree nor disagree, somewhat disagree, strongly disagree
Block 3: Data Sharing			
7	How willing would you be to share your personal health data to help create a Digital Twin for your own healthcare?	5-point Likert scale	Extremely willing, very willing, moderately willing, slightly willing, not at all willing
8	Would you allow your anonymized health data to be used to develop Digital Twin technologies that could help other patients or medical research?	Multiple choice	Yes under the right conditions, Yes unconditionally, Unsure, No
9	Which of the following would make you feel comfortable sharing your health data? (You may select multiple options)	Multiple choice (multiple selections possible)	- My data is anonymized, - There are strong privacy and security measures, - I can give withdraw consent anytime, - It directly improves my own healthcare, - It is managed by a public hospital or university, not by private companies - I would not share my data under any circumstances
10	Would you want to be able to access or delete your digital twin data at any time?	Multiple choice	Yes definitely, Maybe depending on regulations, No I wouldn't need that option, Not sure

Table 18: *Survey Questions Outline*

Q No.	Question	Question Type	Answer Options
Block 4: Trust & Autonomy			
11	Who would you trust more when it comes to making decisions about your treatment?	Multiple choice	- A doctor supported by a Digital Twin system that helps guide decisions - A doctor who relies mainly on traditional experience and methods - Both equally - Not sure
12	In your opinion, what should be the role of doctors when using Digital Twin technology?	Multiple choice	- The doctor should always make the final decision - The Digital Twin and doctor should make decisions together - The Digital Twin should make decisions independently - Not sure
13	What would increase your trust in Digital Twin technology?	Multiple choice (Select up to 2 options)	- Recommendation from my doctor - Approval by national health authorities - Proven success stories from other patients - Transparent data protection rules - Public (Non-commercial) ownership of the system
Block 5: Barriers & Opportunities			
14	What worries you most about Digital Twin technology in healthcare?	Multiple choice	- Data privacy and misuse - Wrong or biased recommendations - Unequal access (only for wealthy or urban patients) - Loss of human contact in care - I have no specific concerns
15	In general, how open are you to new digital technologies in healthcare (e.g. health apps, AI diagnostics, wearables)?	5-point Likert scale	Very open, Rather open, Neutral, Rather skeptical, Very skeptical
16	If you heard media reports about a Digital Twin operation gone wrong, would that reduce your trust in technology?	5-point Likert scale	Strongly agree, somewhat agree, neither agree nor disagree, somewhat disagree, strongly disagree
17	If Digital Twin technology significantly improved your treatment, would you be willing to pay more for such care?	Multiple choice	Yes definitely, Maybe depending on cost, No, Not sure
Block 6: Attention Tracker			
18	To ensure data quality, please select Disagree for this question.	Multiple choice	Agree, Neither agree nor disagree, Disagree

Q No.	Question	Question Type	Answer Options
Block 7: Hospital Digital Twin Scenario			
Scenario: *Now imagine you are in a hospital that uses a Digital Twin – not of a patient, but of the hospital itself. It creates a live digital model of rooms, beds, staff, and patient flow. It helps the hospital reduce waiting times, plan operations more efficiently, and allocate resources better.*			
19	Dou you believe that using a Digital Twin of a hospital (e.g. to manage beds, staff, or patient flow) could improve the overall healthcare experience?	5-point Likert scale	Strongly agree, somewhat agree, neither agree nor disagree, somewhat disagree, strongly disagree
20	If both a hospital and a private technology company had access to your digital twin data, how would that affect your level of trust?	Multiple choice	- I would trust it much less - I would trust it somewhat less - It wouldn't change my trust - I would trust it more - Not sure
21	Do you think Digital twin technology should be available to all hospitals or only specialized centers?	Multiple choice	All hospitals, Only specialized hospitals, Not sure
Block 8: Demographics			
22	How old are you?	Multiple choice (Allowed only one answer)	- Under 18 - 18-24 years old - 25-34 years old - 35-44 years old - 45-54 years old - 55-64 years old - 65+ years older
28	What is your gender?	Multiple choice (Allowed only one answer)	- Male - Female - Non-binary/third gender - Prefer not to say
29	Which industry do you currently work in?	Multiple choice (Allowed only one answer)	- Healthcare - Technology - Education - Public Sector - Retail/Services - Manufacturing - Other - Not currently employed
30	What is your approximate annual income in comparison to your country's average?	Multiple choice (Allowed only one answer)	- Low income - Medium income - High income - Prefer not to say
31	In which country do you currently reside?	Drop Down	All countries of the world
32	Overall, how would you rate the healthcare system in your country?	5-point Likert scale	Very positive, Somewhat positive, Neutral, Somewhat negative, Very negative

Appendix E: Survey Sample Profile and Descriptive Statistics

The appendix summarised the demographic structure and digital readiness of the final survey sample (n = 244) to contextualise the inferential analyses reported in Section 4.3.