The Effect of Remote Patient Monitoring on Quality of Care: The Mediating Role of Real-time Clinical Data Utilization

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Abstract

The increasing demand for improved healthcare outcomes and operational efficiency has catalyzed the adoption of digital technologies in hospital settings. Remote Patient Monitoring (RPM) and real-time clinical data systems have emerged as critical enablers of healthcare transformation and quality enhancement. This study examines the impact of RPM on the Quality of Care (QoC) at Jordan University Hospital, with a particular emphasis on the mediating role of Real-Time Clinical Data Utilization (RTCDU). A cross-sectional quantitative survey was administered to 263 healthcare professionals, including physicians, nurses, and health information administrators. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess direct and mediated relationships among RPM, RTCDU, and perceived QoC.

The results reveal that RPM significantly improves both RTCDU and QoC. Moreover, RTCDU positively influences QoC and mediates the relationship between RPM and QoC. These findings underscore the strategic importance of integrating RPM technologies within a real-time, data-responsive clinical infrastructure. RPM's effectiveness depends on technological deployment and the healthcare system's capacity to operationalize real-time data. The study offers critical insights for health system stakeholders, particularly in low- and middle-income contexts, emphasizing that digital health initiatives must prioritize technological integration and clinical data utilization to achieve sustainable improvements in care quality.

Keywords: Remote Patient Monitoring (RPM); Real-time Clinical Data Utilization; Quality of Care; Digital Health Transformation; Health Informatics.

1. Introduction

Healthcare systems worldwide are facing increasing challenges, including a growing number of people living with chronic illnesses, aging populations, and ongoing shortages of resources. These issues have intensified the need for new, adaptable care models that deliver high-quality, accessible, and sustainable services across different regions (Filip et al., 2022; Guandalini, 2022). Additionally, inefficiencies within the system and a lack of healthcare workers have pushed many health systems to embrace digital solutions to build long-term strength and improve service delivery (Ilin et al., 2022; Kraus et al., 2021).

The shift to digital healthcare includes a range of tools and technologies, such as online consultations, smart data systems, wearable devices, and secure data platforms, all aimed at improving how care is delivered and managed (Mbunge et al., 2021; Pachuary et al., 2025; Haleem et al., 2022). Concepts like Medical 4.0 and Healthcare 5.0 represent this shift toward more personalized, data-informed, and forward-looking care approaches (Stoumpos et al., 2023; Rachmad, 2022).

One key part of this digital evolution is Remote Patient Monitoring (RPM), central to care models prioritizing outcomes and value. RPM allows health professionals to monitor patients from a distance by continuously collecting health data. This enables timely actions, lowers the chance of hospital readmissions, and supports ongoing care outside hospitals or clinics (Delgado, 2022; Bansal et al., 2022). This movement toward remote, tech-supported care fits well with global strategies to enhance care quality while using resources wisely (Petersson et al., 2022; Paul et al., 2023).

However, rolling out RPM effectively requires overcoming several obstacles, such as ensuring different systems can work together, protecting patient data, encouraging staff to use new technologies, and preparing healthcare organizations for change (Ilin et al., 2022; Stoumpos et al., 2023). Furthermore, as digital tools and data-driven methods become more common in clinical care, there is a growing need for clear rules around ethics, patient consent, and smooth integration into day-to-day healthcare routines (Petersson et al., 2022; Okunlaya et al., 2022).

While RPM was first introduced to help manage chronic diseases, it has since grown into a key feature of digital healthcare, offering scalable support for prevention and personalized care (Tan et al., 2024; Holtz et al., 2024). Typically, RPM uses wearable devices, mobile health apps, and internet-connected tools to track vital signs like heart rate, blood pressure, blood sugar, and oxygen levels (Boikanyo et al., 2023; Hayes et al., 2023). These systems create a two-way communication channel between patients and healthcare providers, which helps catch early warning signs, deliver timely care, and adjust treatment plans as needed (Shaik et al., 2023; Patel et al., 2022). When enhanced with intelligent features, RPM can also help identify risks, support decisions, and encourage patients to stick to their treatment plans (Dubey & Tiwari, 2023; Thomas et al., 2021).

Research strongly supports the benefits of RPM. Studies and reviews have shown that it can lower the number of hospital visits and emergency cases, especially for chronic conditions like heart failure, diabetes, and high blood pressure (Taylor et al., 2021; De Guzman et al., 2022). For example, Pritchett et al. (2021) found fewer hospital stays among cancer patients with COVID-19 who participated in RPM programs, showing its usefulness even in urgent care settings. Other findings suggest that RPM improves patient satisfaction, adherence to treatment, and overall well-being (Tan et al., 2024; Pannunzio et al., 2024). Cost analyses further suggest that RPM can be a financially smart investment for health systems aiming to expand its use (De Guzman et al., 2022).

Despite its promise, RPM has not been adopted equally everywhere. Its use depends on the availability of digital infrastructure, payment systems, healthcare provider readiness, and patients' comfort with technology (Alanazi & Daim, 2021; Navathe et al., 2022). Tackling these challenges is crucial to make RPM a standard part of everyday healthcare.

Improving healthcare quality is a key goal for health systems and is increasingly linked to digital upgrades. Major organizations such as the World Health Organization (WHO) and the Agency for Healthcare Research and Quality (AHRQ) define quality care using six key areas: safety, effectiveness, timeliness, patient-centeredness, efficiency, and fairness (Geltmeyer et al., 2025; Azyabi et al., 2021; Aung et al., 2022). RPM contributes to many of these areas by offering real-time monitoring, fast responses, and greater patient involvement (Geltmeyer et al., 2025). With continuous data flow, healthcare teams can make quicker decisions, ensure medications are taken correctly, and improve how long-term conditions are managed—all of which lead to safer and more effective care.

RPM also supports a more patient-focused approach, allowing people to take an active role in their care and work closely with providers when making decisions (Millar et al., 2024).

Regarding timely care, RPM can reduce delays in diagnosis and treatment, especially for those who need ongoing observation. It also boosts efficiency by easing the burden on staff and allowing them to concentrate on tasks that require their expertise (Azyabi et al., 2021; Mahbooba et al., 2021). However, the success of these benefits depends on factors like the strength of digital networks, leadership from clinicians, and the preparedness of staff (Mwale et al., 2024; Al-Atiyyat et al., 2023).

Real-time data is at the core of RPM's success, which has become essential in modern healthcare systems. Access to up-to-date information helps doctors make faster and better decisions by identifying health risks early and acting quickly (Himani et al., 2024; Dagliati et al., 2021). Electronic health records, dashboards, and automatic alerts make this data easier to understand and use (Dixon et al., 2021; Sheikh et al., 2021). This reduces mental strain on providers, encourages team collaboration, and improves patient care over time (Gupta et al., 2022).

However, just having data is not enough—it needs to be accessible, easily shared, and smoothly incorporated into daily clinical activities (Awrahman et al., 2022; Dasaradharami Reddy & Gadekallu, 2023). In RPM, real-time data connects the information gathered from patients with decisions made in hospitals. Without systems to quickly interpret and act on this data, the large volume of information can become overwhelming and reduce RPM's effectiveness (Sheikh et al., 2021; Dagliati et al., 2021). Therefore, using real-time data not only supports RPM operations but also helps improve the quality of care.

While RPM is gaining attention globally, most studies focus on wealthier countries with strong digital infrastructure (Tan et al., 2024; Holtz et al., 2024; Hayes et al., 2023). There is limited research from regions like the Middle East and other developing areas, where digital readiness and policies may vary significantly (Alanazi & Daim, 2021; Kraus et al., 2021; Pachuary et al., 2025). Moreover, most existing research focuses only on direct outcomes like fewer hospital visits or lower costs rather than exploring how factors like real-time data use might influence those results (Taylor et al., 2021; Pannunzio et al., 2024). This lack of in-depth understanding is especially important because digital health relies on complex systems that involve technology, people, and policy working together (Amiri et al., 2024; Awrahman et al., 2022). Ignoring factors such as how clinical workflows are designed, staff training, or organizational culture makes it harder to apply existing findings to different settings (Petersson et al., 2022; Mbunge et al., 2021).

To help fill these gaps, this study looks at how real-time data use affects the link between RPM and care quality, using Jordan University Hospital (JUH) as a case study. As a top teaching hospital in Jordan, JUH offers a useful setting to study RPM in a country still developing its digital health capabilities. The hospital has introduced several digital tools, such as telehealth services and connected monitoring devices, though it still faces challenges like poor system compatibility, limited training, and infrastructure limits (Obeidat & El-Salem, 2021; Alkhwaldi & Abdulmuhsin, 2022; Alarabyat et al., 2023).

Because JUH is a medical school and a leader in digital innovation, it presents a unique opportunity to explore how integrating real-time data affects RPM performance in a setting with limited resources. This research answers global calls for more localized, practical studies on digital health and offers insights that can help guide health policy, management, and digital strategy.

This study specifically aims to assess how RPM influences care quality at JUH, focusing on the role of real-time data as a key factor. Doing so addresses the lack of research in Middle Eastern health systems and offers new insights into the internal processes that make digital health tools effective.

The paper seeks to contribute to a more detailed understanding of how RPM can support better healthcare delivery in regions with growing digital infrastructure. The findings inform policy decisions and practical efforts to improve digital healthcare.

The structure of the paper includes an introduction and literature review, followed by the research question and conceptual framework. It then explains the methods, presents the study results, and discusses key findings, practical implications, and recommendations.

2. Literature Review

2.1 Remote Patient Monitoring (RPM) in Healthcare

Remote Patient Monitoring (RPM) has significantly changed how healthcare is delivered. It allows health professionals to gather patient data outside hospitals or clinics and review it remotely to guide care. Though it was first introduced to help manage long-term illnesses, RPM has become an essential part of smart healthcare. It now includes wearable health trackers, mobile health apps, and digital platforms that monitor patients' vital signs in real-time (Lalrengpuii et al., 2025; Condry & Quan, 2023).

RPM is used in hospital and outpatient settings, though its role differs slightly depending on the environment. In hospitals, RPM helps doctors detect health issues early, lowers the chance of patients being readmitted to intensive care, and supports follow-up care after discharge. This leads to better continuity and less strain on healthcare services (Whitehead & Conley, 2023; Patel et al., 2022). Outside the hospital, RPM is often used to manage chronic diseases like diabetes or heart failure, helping patients stick to their treatment plans, encouraging early responses to symptoms, and increasing involvement in their care (Tan et al., 2024; Hayes et al., 2023). Advanced technologies can also help predict problems, spot unusual patterns, and deliver more personalized care through RPM (Shaik et al., 2023; Ramezani et al., 2025; Bacha & Zainab, 2025).

A growing body of research supports RPM's positive effects on health outcomes. Studies have shown that RPM can improve patient safety, increase the chance of people taking their medications correctly, raise satisfaction, and improve overall life quality (Tan et al., 2024; Pannunzio et al., 2024). For example, Pritchett et al. (2021) found that cancer patients with COVID-19 who were part of an RPM program were hospitalized less often. Broad reviews of the topic also suggest that RPM helps reduce emergency care needs, especially when combined with personalized communication and fast clinical follow-up (Taylor et al., 2021; Thomas et al., 2021).

Beyond improving care, RPM may also offer financial advantages. It can reduce emergency room visits, shorten hospital stays, and prevent costly complications, which is especially helpful in managing chronic illnesses and during health crises like pandemics (De Guzman et al., 2022; Dubey & Tiwari, 2023). Still, the success of RPM depends on strong technology systems, digital skills among users, and smooth integration into everyday medical routines. These requirements can be difficult to meet in underdeveloped or rural areas (Tagne et al., 2025; Boikanyo et al., 2023).

RPM shows great promise and significant hurdles in developing countries, including those with health systems similar to Jordan's. While growing interest in using RPM to close healthcare access gaps, problems like poor internet service, hesitation from medical professionals, and unclear regulations often slow down adoption (Lalrengpuii et al., 2025;

Bouabida et al., 2025). Nevertheless, recent research points to possible solutions, such as adjusting systems to local needs, training healthcare workers, and involving communities and decision-makers in the process (Alanazi & Daim, 2021; Shock, 2025).

2.2 Quality of Care in Modern Healthcare Systems

The quality of care is a critical part of effective health systems. According to the World Health Organization (WHO), quality refers to how well healthcare services help patients achieve the best possible health outcomes while following professional guidelines. One well-known approach to measuring quality comes from Donabedian, who emphasized examining healthcare structures, processes, and outcomes as interconnected elements (Johnson et al., 2022; Takawira et al., 2025).

Today, healthcare quality includes several important areas: safety, effectiveness, patient-centeredness, timeliness, and efficiency. Safety is especially important in emergency or complex care settings, where system failures can have serious consequences, particularly for older adults and people with disabilities (Louch et al., 2021; Millar et al., 2024). Effectiveness focuses on whether treatments are based on sound evidence and are likely to work, which often depends on how well healthcare providers follow protocols (Aung et al., 2022). Patient-centeredness highlights the need to listen to what matters most to patients—their preferences, values, and concerns. Research shows that involving patients in decisions leads to better experiences and results (Khoiro et al., 2025; Okeny et al., 2024).

Timely care and efficient use of resources are also essential, especially in busy or underfunded health systems. When treatments or tests are delayed, patients may get worse or lose confidence in their care providers (Osmanski-Zenk et al., 2024). Efficient systems aim to get the best results with the least waste, often by redesigning workflows or using staff smarter (Mahbooba et al., 2021; Geltmeyer et al., 2025).

Within this broad framework, RPM has the potential to both improve and complicate care quality. On the one hand, it enhances safety by helping catch early signs of decline, especially in patients at high risk or recently discharged from hospitals, which can prevent readmissions (Aman & Qidwai, 2025). It also supports effective treatment by ensuring regular check-ins and timely actions that align with clinical guidelines. Because patients can be monitored from home and receive more personalized attention, RPM strengthens patient-centered care, too (Suman et al., 2025).

On the other hand, RPM presents new concerns. Not all patients have equal access to technology or the skills to use it, which could worsen health gaps and reduce the personal touch in care (Takawira et al., 2025). Relying too much on automated systems might also weaken the human connection between patients and providers, raising questions about ethics, trust, and professional judgment (Mwale et al., 2024). In addition, concerns about data accuracy, keeping information secure, and ensuring systems work well together remain important—especially when RPM tools are not well connected to regular hospital systems (Singh et al., 2025).

Despite these challenges, using RPM as part of hospital quality programs has shown encouraging signs. It can help nurses take on leadership roles, encourage teamwork across departments, and create an environment where safety and continuous improvement are top priorities (Batubara et al., 2021; Al-Atiyyat et al., 2023). However, hospitals need flexible systems that support staff involvement, promote responsibility, and tailor solutions to fit local conditions to make the most of RPM.

2.3 Real-Time Clinical Data Utilization

Real-time clinical data use involves collecting, processing, and applying patient information as soon as it becomes available. This allows healthcare providers to make immediate decisions based on current data. As health systems become more digitized, real-time data has become increasingly important, especially with the growth of electronic health records and the demand for more responsive, personalized care (Himani et al., 2024; Sheikh et al., 2021). Unlike older methods that rely on reviewing past data, this approach allows for more accurate and timely medical actions, helping providers stay ahead of patients' needs.

This type of data comes from various sources. Wearable devices, such as fitness trackers and biosensors, continuously monitor vital signs like heart rate, oxygen levels, and blood sugar—particularly useful for patients outside hospital settings (Amiri et al., 2024). When updated in real-time, Electronic Health Records (EHRs) become active tools that give doctors immediate access to patient history, treatments, and test results (Dagliati et al., 2021). In addition, systems that use connected devices—IoT dashboards—combine patient-generated data into one platform. These allow healthcare teams to oversee multiple patients simultaneously and receive alerts about unusual health changes (Jan et al., 2021; Amadasun et al., 2021).

Including real-time data in everyday medical routines improves the speed and accuracy of care. For example, during the COVID-19 crisis, tools tracking real-time trends helped individual and public health decisions by providing fast, data-driven insights (Dixon et al., 2021). On a personal level, having constant access to updated health information can help catch warning signs early, which reduces hospital stays and improves health outcomes (Gupta et al., 2022; Awrahman et al., 2022).

Real-time data also supports more personalized care. Platforms that analyze this data can help predict future health risks, guide treatment decisions, and adjust care plans based on each patient's specific needs (Dasaradharami Reddy & Gadekallu, 2023). This is especially important in managing long-term conditions, where ongoing monitoring is essential to prevent complications and improve quality of life (Himani et al., 2024).

In Jordan, real-time data use is becoming more common through national digital health projects and telemedicine efforts. These developments are used to strengthen care for chronic diseases and heart conditions. However, progress has been slowed by infrastructure limitations and differences in how well users adapt to the technology (Obeidat & El-Salem, 2021; Alarabyat et al., 2023). Improving internet access, data security, and user engagement with connected health platforms is crucial to making broader adoption possible across the country’s healthcare system (Alkhwaldi & Abdulmuhsin, 2022).

Even with these advancements, challenges remain. Issues such as unreliable data, lack of system compatibility, and limited staff training continue to affect the usefulness of real-time data tools (Amiri et al., 2024; Alarabyat et al., 2023). Moreover, unequal access to digital resources could widen health gaps if not addressed. Therefore, to fully benefit from real-time clinical data, healthcare systems must invest in technology and focus on building the skills, infrastructure, and patient involvement needed to support it effectively.

2.4 Theoretical Framework

The shift toward digital healthcare requires strong theoretical models to guide how new technologies like Remote Patient Monitoring (RPM) and real-time data systems are adopted and used. This study is based on two key models: the Technology Acceptance Model (TAM) and the Information Systems (IS) Success Model. Together, they help explain how users interact with digital health tools and how these tools affect clinical outcomes.

The Technology Acceptance Model, introduced by Davis, suggests that people are more likely to adopt a new technology if they believe it is useful and easy to use. In healthcare, these ideas apply to how doctors, nurses, and patients view the practicality and simplicity of digital tools (Stoumpos et al., 2023). TAM has been widely used to study how health workers in developing systems—like Jordan's—adapt to digital innovations. It offers insights into how factors such as digital skills, workloads, and infrastructure influence using RPM and real-time data tools (Ilin et al., 2022; Alarabyat et al., 2023).

Alongside TAM, the IS Success Model takes a broader view. It looks at six main aspects: the system's quality, the usefulness of the information, the level of service, actual system use, user satisfaction, and the overall benefits gained. This model is especially useful for evaluating systems that handle real-time data, where system performance directly impacts how well decisions are made, and services are delivered (Pachuary et al., 2025; Delgado, 2022). Including this model in the study allows for a deeper understanding of how technology affects the user experience and the organization.

These frameworks are particularly relevant given the complexities of digital healthcare. Simply having the right technology is not enough—systems must also match the institution's readiness, address privacy and security issues, and allow for smooth data sharing (Paul et al., 2023; Kraus et al., 2021). In lower-income countries like Jordan, additional factors such as staff attitudes, patient involvement, and government support play a major role in determining whether digital health programs succeed (Petersson et al., 2022; Mbunge et al., 2021).

By combining TAM and the IS Success Model, this study takes a two-part approach that looks at individual acceptance and system performance. This combination is essential for understanding how real-time data affects the connection between RPM and care quality. It is especially important in hospitals, where clinical tasks vary widely, and the level of digital development can differ from one department to another.

2.5 Hypotheses Development

Remote Patient Monitoring (RPM) has emerged as a prominent strategy for enhancing healthcare quality by extending clinical oversight beyond traditional settings. Its contributions span multiple domains, including patient safety, early detection of clinical deterioration, and preventing avoidable hospitalizations (Taylor et al., 2021; Pritchett et al., 2021). Evidence suggests that RPM programs improve medication adherence, decrease emergency department utilization, and enhance patient self-management, particularly in chronic diseases (Tan et al., 2024; Ramezani et al., 2025). By enabling real-time symptom tracking and facilitating clinician-patient interactions, RPM also fosters personalized care, increasing patient satisfaction and engagement (Holtz et al., 2024; Pannunzio et al., 2024). Furthermore, RPM aligns with the quality dimensions outlined by the World Health Organization (WHO) and the Donabedian framework—specifically efficiency and timeliness (Johnson et al., 2022; Geltmeyer et al., 2025). Studies conducted across diverse settings, from high-income nations to rural and underserved areas, have demonstrated tangible improvements in healthcare delivery following RPM implementation (Bouabida et al., 2025; Tagne et al., 2025). In the broader context of digital transformation, RPM systems represent foundational tools for enabling value-based care and data-driven quality improvement (Stoumpos et al., 2023; Kraus et al., 2021).

Based on the literature, the following hypothesis is proposed:

H1 – *Remote Patient Monitoring has a positive effect on Quality of Care.*

The value of RPM extends beyond remote observation; its clinical efficacy is intrinsically tied to its ability to produce continuous, real-time data streams. Data derived from wearable devices, home-based sensors, and mobile health (mHealth) platforms empower clinicians with timely insights that support more informed decision-making (Condry & Quan, 2023; Amadasun et al., 2021). As a result, RPM is closely linked to real-time clinical data utilization, requiring robust systems for monitoring, analyzing, and visualizing patient data to drive individualized care (Ramezani et al., 2025; Bacha & Zainab, 2025). Studies affirm that RPM data, when incorporated into centralized dashboards, enhances care team responsiveness and improves the accuracy of clinical assessments (Shaik et al., 2023; Tan et al., 2024).

The Internet of Things (IoT) expansion in healthcare has further strengthened the interoperability of RPM systems with broader health information infrastructures, including electronic health records and AI-powered analytics platforms (Mbunge et al., 2021; Jan et al., 2021). In Jordan, the integration of real-time feedback mechanisms into telehealth programs illustrates the growing recognition of this approach, although technical and infrastructural limitations remain (Obeidat & El-Salem, 2021; Alarabyat et al., 2023). Ultimately, RPM's clinical impact depends on the system's capacity to process, interpret, and act upon real-time data, making such utilization a critical operational feature rather than a secondary function (Alkhwaldi & Abdulmuhsin, 2022; Sheikh et al., 2021).

Accordingly, the second hypothesis is proposed:

H2 – *Remote Patient Monitoring positively affects Real-time Clinical Data Utilization.*

Real-time clinical data utilization has become a cornerstone of modern, data-driven healthcare systems, enabling timely, proactive, and individualized interventions. Immediate access to clinical data enhances the precision and responsiveness of care, reducing errors and improving patient safety (Gupta et al., 2022; Dixon et al., 2021). During public health emergencies like the COVID-19 pandemic, real-time data platforms were pivotal in supporting care coordination and optimizing resource allocation (Dagliati et al., 2021; Amiri et al., 2024). These capabilities are particularly valuable in acute and chronic care settings, where delays in clinical action can significantly compromise outcomes.

In hospital environments, real-time data integration facilitates comprehensive clinical decision-making by synthesizing vital signs, laboratory results, and diagnostic records into actionable insights (Awrahman et al., 2022; Himani et al., 2024). When augmented with artificial intelligence and machine learning algorithms, real-time systems can further stratify risk and initiate early interventions (Dasaradharami Reddy & Gadekallu, 2023; Suman et al., 2025). Adopting these tools has been associated with improvements across multiple quality dimensions, including safety, effectiveness, efficiency, and patient satisfaction (Millar et al., 2024; Aman & Qidwai, 2025). In low-resource settings, real-time data utilization is a strategic mechanism to optimize limited healthcare resources (Takawira et al., 2025; Alarabyat et al., 2023).

Thus, the third hypothesis is formulated:

H3 – *Real-time Clinical Data Utilization positively affects the Quality of Care.*

While RPM generates patient-centered data, its clinical value is largely determined by the systems that leverage this data in real-time. Existing studies emphasize that RPM technologies alone do not guarantee improved outcomes unless accompanied by mechanisms for timely data interpretation and clinical action (Thomas et al., 2021; Shaik et al., 2023). Real-time data utilization is a critical conduit, transforming raw inputs into meaningful interventions that reduce mortality and shorter hospital stays and enhance patient experiences (Ramezani et al., 2025; Holtz et al., 2024).

In complex care environments, RPM systems equipped with real-time analytics have demonstrated the ability to improve response times, strengthen team coordination, and enhance the precision of medical decisions (Dixon et al., 2021; Gupta et al., 2022). Conversely, when data generated by RPM is underutilized, the risk of information overload and clinical inertia rises, undermining the return on digital health investments (Sheikh et al., 2021; Pachuary et al., 2025). These findings support the notion that real-time data utilization mediates, mediating and facilitating the translation of RPM outputs into tangible improvements in care quality (Ilin et al., 2022; Petersson et al., 2022).

This leads to the final hypothesis:

H4 – *Real-time Clinical Data Utilization mediates the relationship between Remote Patient Monitoring and Quality of Care.*

2.6 Conceptual Model

In response to the increasing complexity of healthcare systems and the accelerating pace of digital transformation, the conceptual model illustrated in **Figure 1** presents a structured framework linking Remote Patient Monitoring (RPM), Real-time Clinical Data Utilization, and Quality of Care. This model reflects the convergence of emerging digital health technologies with the imperative for patient-centered, data-driven care.

The model's foundation is RPM, which represents the technological input. RPM captures and transmits biometric data to clinicians for real-time evaluation through wearable biosensors, mobile health applications, and telemonitoring platforms. These technologies have effectively improved adherence, reduced hospital readmissions, and promoted proactive, home-based care models (Tan et al., 2024; Pritchett et al., 2021; Lalrengpuii et al., 2025). RPM is increasingly recognized as a key enabler of healthcare decentralization and continuity of care within global health systems (Whitehead & Conley, 2023; Shock, 2025).

Real-time Clinical Data Utilization is situated in the model as an outcome of RPM and a mediator in its relationship with care quality. The digitization of healthcare processes has foregrounded the importance of real-time data applications—including alerts, dashboard analytics, and integration with electronic health records—for timely and effective clinical response (Himani et al., 2024; Dagliati et al., 2021). When RPM-generated data is rapidly processed and deployed, its value in supporting decision-making and improving clinical outcomes is substantially amplified (Shaik et al., 2023; Dixon et al., 2021). This positioning aligns with broader trends toward intelligent, learning health systems powered by AI, IoT, and federated data infrastructures (Dasaradharami Reddy & Gadekallu, 2023; Amiri et al., 2024).

Quality of Care, the model's dependent construct, encapsulates the desired healthcare outcomes influenced by technological innovation and data utilization. Drawing on the WHO and Donabedian's quality dimensions—safety, effectiveness, timeliness, and patient-centeredness—the model posits that real-time insights derived from RPM data enhance care coordination, diagnostic accuracy, and patient satisfaction (Johnson et al., 2022; Millar et al., 2024). When real-time data systems are embedded within care workflows, quality improvements are consistently observed in diverse clinical contexts (Tan et al., 2024; Holtz et al., 2024; Pannunzio et al., 2024).

From a systems perspective, the conceptual model reflects the ongoing evolution toward intelligent health ecosystems. Its successful implementation depends on enabling conditions such as robust digital infrastructure, system interoperability, and clinician engagement (Ilin et al., 2022; Kraus et al., 2021). However, persistent barriers—including fragmented data systems, organizational resistance, and cybersecurity risks—must be addressed to ensure that technological potential translates into sustained improvements in care quality (Paul et al., 2023; Petersson et al., 2022; Pachuary et al., 2025).

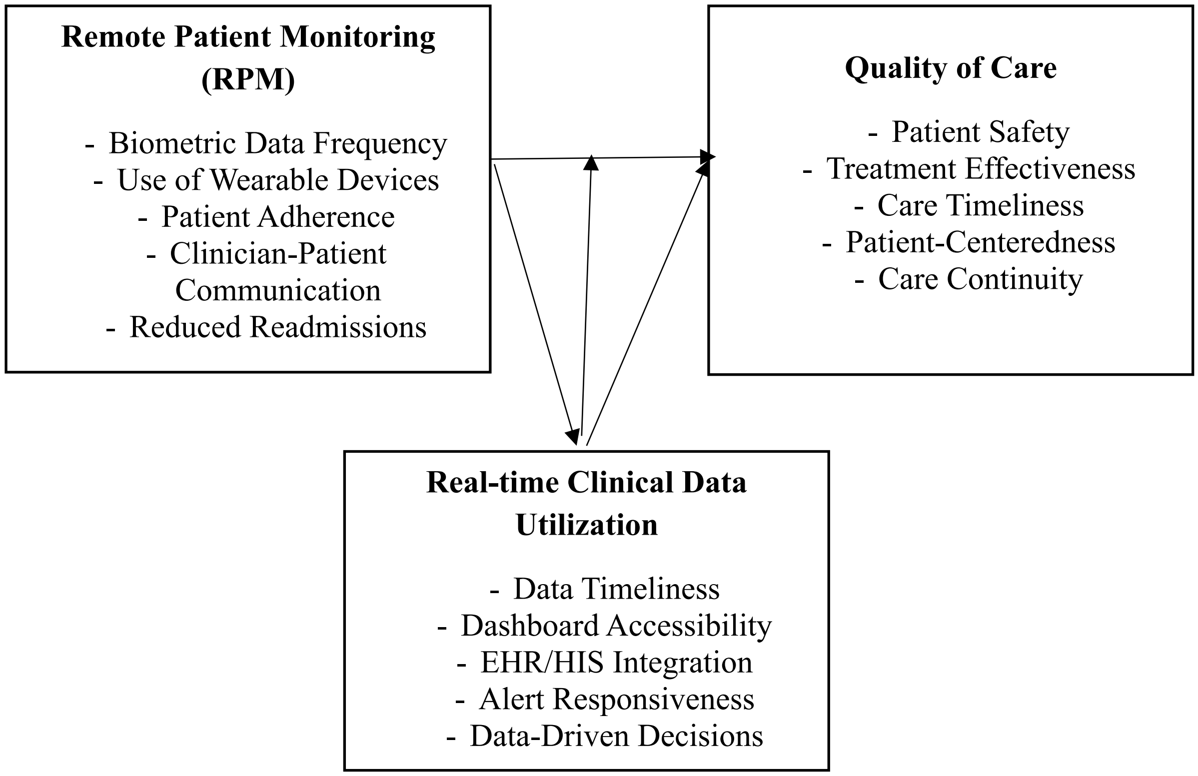

Figure 1: Conceptual Model

3. Methodology

3.1 Research Design

This study adopted a quantitative, cross-sectional research design to investigate the impact of remote patient monitoring (RPM) on quality of care, with particular attention to the mediating effect of real-time clinical data utilization (Creswell, 2014). A quantitative approach was deemed appropriate as it facilitates objective measurement and statistical testing of hypothesized relationships among variables (Saunders et al., 2019). This approach is widely utilized in health informatics research, where structured data analysis is fundamental for identifying empirical patterns (Bowling, 2014).

The cross-sectional nature of the design enabled data collection at a single point in time, which is advantageous for assessing prevailing perceptions and practices without requiring longitudinal follow-up (Alvesson & Sandberg, 2013). This temporal efficiency is particularly beneficial in dynamic healthcare settings where timely insights are essential for implementing digital health technologies and service improvement initiatives (Venkatesh et al., 2003). Moreover, cross-sectional survey designs are well-established in studies examining technology adoption and mediating constructs such as clinical data utilization (Creswell, 2014; Saunders et al., 2019).

3.2 Population and Sampling

The target population comprised the entire medical workforce at Jordan University Hospital (JUH), totaling 2,021 healthcare professionals. This included physicians, nurses, and health information administrators directly involved in patient care and using RPM systems and clinical data platforms.

To ensure adequate representation, a stratified non-probability sampling technique was employed. Stratification was based on professional roles—physicians, nurses, and health information administrators—reflecting their distinct contributions to clinical technologies (Etikan & Bala, 2017). Within each stratum, convenience sampling was applied to recruit eligible participants available during the data collection period.

Sample size estimation was conducted using Cochran's formula, assuming a 95% confidence level, 5% margin of error, and a 50% response distribution (Israel, 1992), yielding a minimum required sample of 323. Due to logistical constraints, a final sample of 280 participants was selected. This figure remains within acceptable limits for generalizability in health research (Krejcie & Morgan, 1970).

Inclusion criteria encompassed (1) current employment at JUH, (2) direct involvement in clinical care or digital health systems, and (3) a minimum of six months of continuous service. Exclusion criteria included administrative personnel without interaction with clinical systems and staff on extended leave during the study period.

Of the 280 distributed questionnaires, 263 valid responses were retained after data cleaning, resulting in a response rate of 94%, thereby enhancing the statistical power and credibility of the findings (Babbie, 2020). Table 1 summarizes the study population and sample distribution.

Table 1. Study Population and Sample Summary

Professional Group	Estimated Population	Sample Size (Surveyed)	Valid Responses
Physicians	720	100	95
Nurses	1,100	140	132

Health Info Administrators	201	40	36
Total	**2,021**	**280**	**263**

3.3 Instrumentation and Measurement

A structured questionnaire served as the primary data collection instrument, designed to assess three key constructs: Remote Patient Monitoring (RPM), Real-time Clinical Data Utilization, and Quality of Care. Items were adapted from established theoretical frameworks and empirical studies in health informatics and healthcare quality (DeLone & McLean, 2003; Donabedian, 1988; Venkatesh et al., 2003). Responses were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), allowing for the quantification of perceptions, behaviors, and attitudes.

The RPM construct (independent variable) comprised 20 items distributed across five sub-dimensions: *Biometric Data Frequency, Use of Wearable Devices, Patient Adherence, Clinician-Patient Communication*, and *Reduced Readmissions*, grounded in telehealth literature (Krick et al., 2019; Kitsiou et al., 2017).

The mediating construct, *Real-time Clinical Data Utilization*, was also measured using 20 items, categorized into five sub-domains: *Data Timeliness, Dashboard Accessibility, EHR/HIS Integration, Alert Responsiveness*, and *Data-Driven Decision Making* (Zhou et al., 2019; Adler-Milstein et al., 2015).

The dependent variable, *Quality of Care*, included 20 items reflecting five core dimensions derived from recognized healthcare quality models: *Patient Safety, Treatment Effectiveness, Care Timeliness, Patient-Centeredness*, and *Care Continuity* (Donabedian, 1988; Institute of Medicine, 2001).

The initial English version of the questionnaire underwent expert review by three healthcare management and informatics scholars for content validity. Following minor revisions, a pilot test with 30 healthcare professionals—excluded from the main study—was conducted. Feedback from the pilot informed item refinement and confirmed instrument reliability.

3.4 Validity and Reliability

Content validity was ensured through expert review focusing on item clarity, relevance, and contextual appropriateness for the Jordanian healthcare setting, in line with best practices for instrument development (Boateng et al., 2018).

Construct validity was assessed using Exploratory Factor Analysis (EFA) with Principal Component Analysis and Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure was 0.88, and Bartlett's Test of Sphericity was statistically significant ($p < .001$), indicating sampling adequacy for factor analysis (Field, 2013). All items loaded significantly (≥ 0.60) on their respective factors, confirming construct validity.

Reliability was evaluated through Cronbach's Alpha and Composite Reliability (CR). All constructs exceeded recommended thresholds ($\alpha > 0.80$; CR > 0.85), demonstrating strong internal consistency (Hair et al., 2019). Reliability metrics are presented in Table 2.

To mitigate common method bias, Harman's single-factor test was conducted. The first unrotated factor accounted for 31.6% of the variance, well below the 50% threshold, indicating minimal risk of bias (Podsakoff et al., 2003).

Table 2. Construct Reliability Metrics

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)
Remote Patient Monitoring (RPM)	0.88	0.91
Real-time Clinical Data Utilization	0.87	0.90
Quality of Care	0.89	0.92

Note: All values exceed $\alpha > 0.70$ and CR > 0.70, as per Hair et al. (2019).

3.5 Data Collection Procedure

Data were collected through a structured, self-administered questionnaire distributed to healthcare professionals at JUH. A hybrid collection method was utilized, incorporating digital (online forms via institutional email and WhatsApp groups) and paper-based formats (distributed during staff meetings and training sessions) to maximize accessibility and response rates.

The data collection period spanned six weeks, from January to mid-February 2025, providing sufficient time for follow-up reminders and clarification of participant queries. Completion time was estimated at 15–20 minutes.

Before distribution, ethical approval was obtained from the affiliated academic institution's Institutional Review Board (IRB). Participation was voluntary, and informed consent was secured from all respondents. Anonymity and confidentiality were strictly maintained, and no personally identifiable information was collected. All procedures adhered to the ethical principles outlined in the Declaration of Helsinki (World Medical Association, 2013).

3.6 Data Analysis Techniques

A multi-step quantitative analysis strategy was employed. Descriptive statistics (means, standard deviations, and frequency distributions) were initially computed to summarize respondent demographics and key variables (Field, 2013).

Subsequently, Structural Equation Modeling (SEM) using SmartPLS 4.0 was applied to assess both the measurement model (construct validity and reliability) and the structural model (hypothesized relationships). Partial Least Squares SEM (PLS-SEM) was selected due to its robustness in handling complex models with mediation, small-to-moderate sample sizes, and non-normal data distributions (Hair et al., 2019). This method is particularly relevant in predictive modeling within health technology research.

To evaluate the mediating role of real-time clinical data utilization, a bootstrapping procedure with 5,000 resamples was conducted. An indirect effect was considered significant if the bias-corrected confidence interval excluded zero (Preacher & Hayes, 2008). Model diagnostics included Variance Inflation Factor (VIF) checks and fit indices such as Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) to ensure model robustness. All analyses were conducted using SmartPLS 4.0 and IBM SPSS Statistics 28.0.

4. Results

4.1 Descriptive Statistics

4.1.1 Respondents' Demographic Profile

Table 3 presents the demographic characteristics of the 263 respondents. The gender distribution was relatively balanced, with females comprising 56.3% (n = 148) and males

43.7% (n = 115), reflecting the gender dynamics typical of healthcare environments, particularly in nursing.

Most respondents were between 31 and 40 (42.2%), followed by those aged 41–50 (25.1%). Participants aged 21–30 represented 22.4%, while those over 50 accounted for 10.3%. This age distribution suggests a predominance of mid-career professionals, potentially offering a range of insights shaped by varying levels of experience.

In terms of professional roles, nurses constituted the largest group (50.2%), followed by physicians (36.1%) and health information administrators (13.7%). This distribution supports a multi-disciplinary perspective central to the study's objectives.

Regarding professional experience, 39.2% had 6–10 years of experience, 29.3% had 11–15 years, and 20.2% reported more than 15 years. Respondents with less than 5 years of experience made up 11.4%. Collectively, the sample reflects a diverse and experienced workforce relevant to the study's focus on remote patient monitoring (RPM) and real-time clinical data utilization.

Table 3: *Demographic Profile of Respondents (N = 263)*

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	115	43.7
	Female	148	56.3
Age Group	21–30 years	59	22.4
	31–40 years	111	42.2
	41–50 years	66	25.1
	Above 50 years	27	10.3
Professional Role	Physicians	95	36.1
	Nurses	132	50.2
	Health Info Administrators	36	13.7
Years of Experience	Less than 5 years	30	11.4
	6–10 years	103	39.2
	11–15 years	77	29.3
	More than 15 years	53	20.2

Note: Percentages may not total 100% due to rounding.

4.1.2 Descriptive Statistics for Study Constructs

Table 4 summarizes the descriptive statistics for the three core constructs.

The mean Remote Patient Monitoring (RPM) score was 3.87 (SD = 0.62), indicating generally positive perceptions regarding integrating RPM tools in clinical workflows. The moderate variability suggests differing levels of exposure or departmental implementation. Real-time Clinical Data Utilization exhibited a higher mean of 3.94 (SD = 0.58), reflecting consistent perceptions of data-driven decision-making practices across the sample. The relatively low standard deviation points to the widespread adoption of real-time data tools like dashboards and alerts.

Quality of Care received the highest mean score at 4.03 (SD = 0.55), suggesting strong agreement among respondents regarding the effectiveness, safety, and patient-centeredness of current service delivery.

Table 4: *Descriptive Statistics of Study Constructs (N = 263)*

Construct	Mean (M)	Standard Deviation (SD)
Remote Patient Monitoring (RPM)	3.87	0.62
Real-time Clinical Data Utilization	3.94	0.58
Quality of Care	4.03	0.55

Note: All constructs are measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

4.2 Measurement Model Assessment

Before hypothesis testing, the measurement model was assessed for reliability and validity to ensure the robustness of the latent constructs, following the guidelines of PLS-SEM (Hair et al., 2019).

4.2.1 Reliability and Convergent Validity

Internal consistency reliability was evaluated using Cronbach's Alpha and composite reliability (CR). Convergent validity was assessed through Average Variance Extracted (AVE). Thresholds of $\alpha \geq 0.70$, CR ≥ 0.70, and AVE ≥ 0.50 were used as criteria for adequacy (Fornell & Larcker, 1981; Hair et al., 2019).

As shown in Table 5, all constructs demonstrated high internal consistency, with Cronbach's Alpha ranging from 0.87 to 0.89 and CR values between 0.90 and 0.92. AVE values exceeded 0.60 for all constructs, confirming satisfactory convergent validity. These results support the reliability and validity of the measurement model, justifying further structural analysis.

Table 5: *Reliability and Convergent Validity of Constructs (N = 263)*

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Remote Patient Monitoring (RPM)	0.88	0.91	0.63
Real-time Clinical Data Utilization	0.87	0.90	0.61
Quality of Care	0.89	0.92	0.65

Note: All values exceed recommended thresholds for reliability and validity.

4.2.2 Indicator Loadings

Indicator loadings represent the strength of the association between each observed item and its underlying latent construct. Loadings above 0.70 are preferred in confirmatory models, although values above 0.60 are acceptable in exploratory contexts (Hair et al., 2019; Hulland, 1999).

As summarized in Table 6, all indicators demonstrated acceptable loadings, ranging from 0.68 to 0.84. Items RPM3 (0.84) and RTD4 (0.82), associated with clinician-patient communication and data-driven decision-making, respectively, exhibited the highest loadings within their constructs. No cross-loadings or misaligned indicators were detected, confirming that each item reliably reflects its corresponding latent variable. These results support the construct validity of the measurement model.

Table 6: *Indicator Outer Loadings by Construct (Selected Items, N = 263)*

Construct	Item Code	Indicator Description (Shortened)	Loading
Remote Patient Monitoring	RPM1	Frequency of biometric data transmission	0.78
	RPM2	Use of wearable devices	0.74
	RPM3	Clinician-patient communication	0.84
	RPM4	Patient adherence to remote instructions	0.68

Real-time Clinical Data Util.	RTD1	Data timeliness	0.75
	RTD2	Dashboard accessibility	0.72
	RTD3	Alert responsiveness	0.77
	RTD4	Data-driven decisions	0.82
Quality of Care	QoC1	Patient safety	0.83
	QoC2	Treatment effectiveness	0.76
	QoC3	Care timeliness	0.79
	QoC4	Continuity of care	0.81

Note: All loadings exceed the recommended threshold of 0.60.

4.2.3 Discriminant Validity

Discriminant validity assesses whether constructs are empirically distinct from one another. Two complementary methods were employed: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

A. Fornell-Larcker Criterion

Discriminant validity is confirmed if the square root of a construct's AVE exceeds its correlations with other constructs (Fornell & Larcker, 1981). As shown in Table 7, all constructs satisfied this condition, with diagonal values (√AVE) exceeding the respective inter-construct correlations, thereby supporting discriminant validity.

Table 7: *Fornell-Larcker Discriminant Validity Matrix*

Construct	RPM	RTCDU	QoC
Remote Patient Monitoring (RPM)	**0.79**		
Real-time Clinical Data Util.	0.62	**0.78**	
Quality of Care	0.58	0.66	**0.81**

Note: Diagonal values (in bold) represent the square roots of AVE.

B. Heterotrait-Monotrait Ratio (HTMT)

The HTMT criterion provides a stricter test of discriminant validity, with values below 0.85 indicating that constructs are empirically distinct (Henseler et al., 2015). As shown in Table 8, all HTMT values were well below the threshold, further confirming discriminant validity.

Table 8: *HTMT Ratios for Discriminant Validity*

Construct Pair	HTMT Value
RPM – RTCDU	0.72
RPM – QoC	0.67
RTCDU – QoC	0.76

Note: All values fall below the conservative threshold of 0.85.

4.3 Structural Model Assessment

Following the validation of the measurement model, the structural model was evaluated for multicollinearity, path relationships, explanatory power (R^2), and mediation effects. This section begins with collinearity diagnostics to ensure the robustness of path coefficient estimates.

4.3.1 Collinearity Diagnostics

Multicollinearity among predictor constructs was assessed using the Variance Inflation Factor (VIF). Values below 5.0 indicate that collinearity is not a concern in PLS-SEM models (Hair et al., 2019).

As reported in Table 9, all VIF values ranged from 1.00 to 1.76, well below the critical threshold. These results confirm that the predictor variables are sufficiently independent, and multicollinearity does not bias the estimation of path coefficients.

Table 9: *Collinearity Statistics (VIF Values)*

Endogenous Construct	Predictor Variable	VIF
Quality of Care	Remote Patient Monitoring	1.76
	Real-time Clinical Data Util.	1.68
Real-time Clinical Data Util.	Remote Patient Monitoring	1.00

Note: All VIF values are below the recommended threshold of 5.0.

4.3.2 Path Coefficients and Hypothesis Testing

Path analysis was conducted to test the hypothesized relationships among constructs. As summarized in Table 10, Remote Patient Monitoring (RPM) had a significant positive effect on Quality of Care (QoC) ($\beta = 0.29$, $t = 4.36$, $p < 0.001$), supporting Hypothesis 1 (H1). This suggests that higher adoption of RPM technologies improves care timeliness, safety, and effectiveness. Hypothesis 2 (H2) was also supported, with RPM exerting a strong positive effect on Real-time Clinical Data Utilization (RTCDU) ($\beta = 0.55$, $t = 8.91$,

$p < 0.001$). This indicates that RPM facilitates the generation and integration of patient data into clinical systems, enhancing real-time responsiveness. Hypothesis 3 (H3) examined the impact of RTCDU on QoC, yielding a significant positive relationship ($\beta = 0.41$, $t = 6.25$, $p < 0.001$). This underscores the role of timely data access in supporting high-quality, coordinated care.

Table 10: *Path Coefficients and Hypothesis Testing Results*

Hypothesis	Path	β	*t*-value	*p*-value	Result
H1	RPM → QoC	0.29	4.36	< 0.001	Supported
H2	RPM → RTCDU	0.55	8.91	< 0.001	Supported
H3	RTCDU → QoC	0.41	6.25	< 0.001	Supported

4.3.3 Coefficient of Determination (R^2)

The coefficient of determination (R^2) indicates the proportion of variance in an endogenous variable explained by its predictors. As shown in Table 11, RPM explained 30% of the variance in RTCDU ($R^2 = 0.30$), reflecting moderate predictive power. Additionally, 52% of the QoC variance was explained by RPM and RTCDU ($R^2 = 0.52$), indicating substantial explanatory strength.

These values confirm the model's predictive adequacy and justify further mediation analysis.

Table 11: *R^2 Values for Endogenous Variables*

Endogenous Variable	Predictor(s)	R^2 Value	Interpretation
Real-time Clinical Data Utilization	RPM	0.30	Moderate
Quality of Care	RPM, RTCDU	0.52	Substantial

Note: R^2 values interpreted per Cohen (1988); model estimated via SmartPLS 4.0.

4.4 Mediation Analysis

Hypothesis 4 (H4) posited that Real-time Clinical Data Utilization mediates the relationship between Remote Patient Monitoring and Quality of Care. A bootstrapping procedure with 5,000 resamples was conducted to test the indirect effect. As shown in Table 12, the indirect path (RPM → RTCDU → QoC) was significant ($\beta = 0.23$, $t = 4.97$, $p < 0.001$), with a 95% bias-corrected confidence interval of [0.15, 0.33], excluding zero. These results confirm the presence of a statistically significant mediation effect. This indicates that RPM contributes to QoC through direct mechanisms and indirectly via enhanced data utilization. Effective integration of RPM with real-time clinical decision-making systems amplifies its impact on care quality.

Table 12: *Mediation Analysis Results (Bootstrapped, 5,000 Resamples)*

Path (Indirect)	β	*t*-value	*p*-value	95% CI	Result
RPM → RTCDU → QoC	0.23	4.97	< 0.001	[0.15, 0.33]	Mediation Supported

Note: Mediation confirmed via non-zero bootstrapped confidence intervals (SmartPLS 4.0).

4.5 Model Fit Indices

Although PLS-SEM prioritizes prediction over model fit, select indices can be used to assess the overall adequacy of the model. Table 13 reports key fit indices, including the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). The SRMR was 0.061, below the recommended threshold of 0.08, indicating a good fit. The NFI was 0.91, suggesting acceptable model performance relative to a null model. Additional indices (d_ULS and d_G) were also within acceptable ranges, further supporting the model's empirical validity. These results confirm that the structural model adequately represents the underlying data and supports the hypothesized relationships among constructs.

Table 13: *Model Fit Indices (SmartPLS 4.0 Output)*

Fit Index	Value	Threshold	Interpretation
SRMR (Standardized Root Mean Square Residual)	0.061	< 0.08	Good fit
NFI (Normed Fit Index)	0.91	Closer to 1 = better	Acceptable fit
d_ULS (Unweighted Least Squares Discrepancy)	0.358	Lower = better	Within acceptable range
d_G (Geodesic Discrepancy)	0.244	Lower = better	Within acceptable range

5. Discussion

This study investigated the interrelationships among Remote Patient Monitoring (RPM), Real-Time Clinical Data Utilization (RTCDU), and Quality of Care (QoC) within a hospital setting. The findings demonstrate that RPM exerts a significant and direct influence on RTCDU and QoC, while RTCDU emerges as a significant predictor of QoC. Notably, RTCDU mediates the relationship between RPM and QoC, underscoring the pivotal role of real-time data utilization in translating digital health capabilities into measurable improvements in patient care.

The positive association between RPM and QoC aligns with a growing literature on healthcare digitalization. Prior studies have emphasized RPM's role in enhancing clinical decision-making, ensuring care continuity, and improving patient adherence—core components of high-quality hospital care (Tan et al., 2024; Holtz et al., 2024). Additional evidence by Pritchett et al. (2021) and Patel et al. (2022) further supports the contribution of RPM to reducing hospital readmissions and enhancing patient safety, particularly among high-risk groups such as oncology and COVID-19 patients. The present findings extend these insights within the context of a middle-income country, illustrating the global applicability of RPM in advancing care quality.

In the Jordanian healthcare context, these outcomes resonate with global observations on the capacity of digital health tools to bridge care delivery gaps and bolster clinical responsiveness in complex hospital environments (Thomas et al., 2021; Shaik et al., 2023). However, as noted in recent literature, persistent barriers—including infrastructural limitations and interoperability challenges—remain particularly salient in resource-constrained settings (Tagne et al., 2025; Alarabyat et al., 2023). Addressing these structural deficiencies is essential to unlocking the full potential of digital health interventions.

The significant relationship between RPM and RTCDU further reinforces the conceptualization of RPM not as an isolated monitoring modality but as an integral component of a broader digital health infrastructure. This corroborates findings by Lalrengpuii et al. (2025), who emphasize that RPM generates high-frequency clinical data that necessitates real-time processing to inform timely interventions. Similarly, the results support the view of RPM as a key node within an interconnected informatics ecosystem, wherein data must flow seamlessly across platforms to support dynamic clinical decision-making (Himani et al., 2024; Awrahman et al., 2022).

The importance of this integration is further supported by Delgado (2022) and Kraus et al. (2021), who contend that the utility of RPM is contingent on the availability of real-time data infrastructure. Within the Jordanian context, this finding reflects persistent global challenges such as data standardization, clinician adoption, and system interoperability (Alkhwaldi & Abdulmuhsin, 2022; Petersson et al., 2022), highlighting the need for targeted investments in digital health infrastructure.

The robust association between RTCDU and QoC underscores the strategic role of health informatics in enabling high-performance clinical environments. This finding is consistent with Sheikh et al. (2021), who advocate for a "learning health system" paradigm in which real-time data informs continuous quality improvement. Further corroboration is found in Dixon et al. (2021) and Dagliati et al. (2021), who demonstrate that real-time access to structured clinical information facilitates accurate diagnoses, reduces treatment delays, and enhances patient-centered care delivery.

Particularly in settings like Jordan University Hospital, where digital integration is ongoing, the utility of real-time dashboards, clinical alerts, and decision support tools represents a tangible opportunity to enhance operational efficiency and long-term planning. This aligns with findings by Gupta et al. (2022) and Amiri et al. (2024), who highlight the growing centrality of real-time informatics in care quality frameworks across both high- and middle-income healthcare systems.

Of particular significance is the mediating role of RTCDU in the relationship between RPM and QoC. This finding affirms that the effectiveness of RPM in improving care outcomes is substantially amplified when real-time data is actively utilized in clinical decision-making. This aligns with theoretical frameworks such as DeLone and McLean's IS success model and supports empirical insights from Ramezani et al. (2025) and Bacha and Zainab (2025), who emphasize the critical role of system integration in realizing the value of digital health tools.

From a digital transformation standpoint, this mediation underscores the need to conceptualize RPM as part of a synergistic digital ecosystem rather than a standalone solution. This is congruent with the perspectives of Ilin et al. (2022) and Pachuary et al.

(2025), who argue that the success of healthcare digitalization depends equally on technological implementation and data operationalization. The layered digital model described by Mbunge et al. (2021) and Bansal et al. (2022) reinforces that continuous, bi-directional data exchange among devices, systems, and providers is foundational to a fully functional digital health ecosystem.

Moreover, these findings align with international imperatives to address digital fragmentation and enhance real-time interoperability in healthcare systems. Guandalini (2022) and Stoumpos et al. (2023) assert that digital transformation must transcend technology deployment to encompass workflow integration, clinician engagement, and data-informed decision support. This is particularly relevant in developing health systems, where infrastructural, organizational, and human capital constraints may impede seamless integration (Obeidat & El-Salem, 2021).

The practical implications of this study are significant. The findings suggest that healthcare leaders should prioritize investments in RPM technologies and the backend infrastructure required to support real-time data capture, analysis, and utilization. This includes the development of interoperability standards, clinician training in digital literacy, and deploying integrated health informatics platforms. As Delgado (2022) highlighted, without a robust data backbone comprising advanced connectivity protocols and smart platforms, the transformative potential of digital healthcare will remain unrealized.

6. Conclusion

This study examined the interrelationships among Remote Patient Monitoring (RPM), Real-Time Clinical Data Utilization (RTCDU), and Quality of Care (QoC) in a tertiary academic hospital in Jordan. Anchored in established frameworks from health informatics and digital transformation literature, the findings confirm that RPM not only exerts a direct positive influence on perceived QoC but also significantly enhances the utilization of real-time clinical data. Critically, RTCDU was found to mediate the relationship between RPM and QoC, indicating that the clinical value of RPM is maximized when embedded within a responsive, data-driven care environment.

These results contribute to the expanding body of evidence supporting the integration of digital health technologies in hospital settings, particularly within low- and middle-income countries undergoing healthcare modernization. The study reinforces the premise that the benefits of RPM are contingent not solely on the availability of technology but on the presence of interoperable systems capable of real-time data capture, interpretation, and clinical application.

From a practical standpoint, the findings highlight the necessity of investing in digital infrastructures that facilitate seamless data flow between RPM systems and clinical decision-making platforms. This directly affects healthcare administrators, policymakers, and health IT professionals seeking to implement scalable, sustainable digital health interventions.

Future research should prioritize longitudinal and multi-site investigations to assess RPM-enabled care's long-term clinical and operational impacts. Additionally, integrating objective system-level metrics alongside qualitative feedback from clinicians and patients could yield deeper insights into successful digital transformation's organizational and behavioral determinants.

In conclusion, this study provides empirical support for a more cohesive, data-integrated digital healthcare model. It underscores that the transformative potential of RPM can only be fully realized within an ecosystem that supports real-time data utilization, informed decision-making, and continuous system learning.

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