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Foreword

Dear readers,

The international conference DigiHealthDayS has become a renowned global forum for education, research, innovation, and networking in Digital Health, held annually. Following each conference, a collection of papers is published as a special proceedings issue under the auspices of the Journal of Applied Interdisciplinary Research (JAIR), with this year marking its fourth edition.

We are delighted to present this special issue, running parallel to our regular annual issue. It gathers selected contributions from the conference, which was founded and is led by Prof. Dr. Georgi Chaltikyan, Head of the WHO Collaborating Centre for Digital Health at the European Campus Rottal-Inn, Studiengangsleiter of the Master of Digital Health, and founder of the DigiHealthDay series. In February 2025, the WHO Regional Office for Europe designated the European Campus Rottal-Inn as the German WHO Collaborating Centre for Digital Health, and to date the only such centre dedicated to Digital Health Education, so it is a genuine pleasure to bring this collaboration to print.

For this special issue, the guest editor and the conference organizing team were responsible for selecting the contributions and for peer review, assuring their academic quality. The peer review was therefore not double-blind.

The Journal of Applied Interdisciplinary Research (JAIR) is an academic journal that aims to provide a current and international overview of interdisciplinary research carried out in an applied manner. As this is a growing field, it warrants a dedicated journal of its own. With the boundaries between academic disciplines increasingly overlapping, we are glad to give researchers an opportunity to publish their interdisciplinary work in a journal devoted to advancing this field and committed to the exchange of ideas across disciplines.

Since this year, JAIR has been listed in the Diamond Discovery Hub (DDH), reflecting our continued belief in open science and open access. The DDH is a registry of scholar-led open access journals. To become a member, a journal must fulfil the following Diamond criteria: persistent identification, scholarly standing, open access under open licenses, no fees, openness to all authors, and community ownership.

The JAIR is generally published annually as an online-only issue. The present print version is a reprint of the online issue; please cite the articles as published online, indicating their respective DOI.

With warm regards,
Your JAIR editors,

Prof. Dr. Michelle J. Cummings-Koether Dr. Kristin Seffer

CONTENT

FOREWORD 5
Michelle Cummings-Koether & Kristin Seffer

GUEST EDITORIAL
Dipak Kalra, Horst Kunhardt, Georgi Chaltikyan, Ozar Mintser, Aninha Fernandes 8

SCIENTIFIC PAPERS
Theme: Digital Health Innovation and Entrepreneurship
Kimia Bajelan, Raul M. S. Laureano, André Lourenço 10
Business Models in Digital Health: Bibliometric and Systematic Review Focusing on Financial, Regulatory, and Adoption Aspects

Felipe de Souza Ricci, Paulo Schor 25
Bridging Gaps in Healthcare Innovation: A Systematic Review of Design Methodologies for Problem Discovery in Technological Health Products

Theme: AI Research
Damla Özyürek, Aslı Suner 42
Enhancing Dirty Data Detection via Large Language Models: Comparative Insights from ChatGPT, Gemini and Copilot

Theme: EHR and Health Information Systems
Yasaman Rasouli, Grigor Chakmishyan, Samir Irshai, Adam Abu-Hilal, Niloufar Ramezanzadegan, Bhanu Singh, Georgi V. Chaltikyan 53
Current Practices and Potential Technological Advancements in Multidisciplinary Tumor Board Workflows: A Scoping Review

Theme: Delivery Models, Bottlenecks, and Moving Forward
Georgi V. Chaltikyan, Mahmoud Abuaysheh, Rousl Al-Sardy, Grigor Chakmishyan, Dmitry Etin, Eugenia Lvova 71
10P-Health: A Conceptual Framework for Continuous, Digitally Enabled Precision Health and Wellness

Rousl Al-Sardy, Georgi V. Chaltikyan, Dmitry Etin, Mahmoud Abuaysheh, Grigor Chakmishyan, Eugenia Lvova 81
Public Readiness for a Personalized Digital Health Platform in Bavaria (10P-Health): A Cross-Sectional Survey of Operational, Legal, Technological, and Stakeholder Determinants of Perceived Feasibility

Theme: Digital Health Innovation and Entrepreneurship
Grigor Chakmishyan, Rousl Al-Sardy, Mahmoud Abuaysheh, Eugenia Lvova, Dmitry Etin, Georgi V. Chaltikyan 98
Continuous, Person-Centered Digital Precision Health and Wellness: A Structured Narrative Review Informing 10P-Health

Theme: Reflections and Perspectives on Digital Health

Birgit Bauer 114
Building Digital Health Literacy in Health: About a Hen, an Egg and Why Usage is not Understanding

Lars Lindsköld, Martin Gerdes, Camila Tomikawa, Birgit Bauer, Rudolf Wagner, Tatyana Kanzaveli 117
Generative AI in the Clinic – Hype, Hope and Reality

IMPRINT 122

Guest Editorial

The **International Congress DigiHealthDayS-2025**, held at the European Campus Rottal-Inn (ECRI), Deggendorf Institute of Technology, once again served as a Global Forum for Education, Research, Innovation, and Networking in Digital Health. Under the overarching theme *"Global Digital Health – today, tomorrow, and beyond"*, this 6th edition brought together leaders, experts, and students from across the world. Participants engaged in a unique convergence of perspectives with keynote addresses from eminent speakers, thought-provoking student presentations, and lively dialogue sessions.

Featured Papers

The four selected papers in this year's collection span three thematic areas: Digital Health innovation and entrepreneurship, AI research, and electronic health records (EHR) and health information systems.

Opening the section on *Digital Health Innovation and Entrepreneurship* is a bibliometric and systematic review of articles that examine why so many digital health solutions fail to progress beyond the pilot stage. Research focus has shifted from foundational technologies such as telemedicine toward strategic dimensions such as value creation, data privacy, and health policy, yet reimbursement, cost structure, licensing, and customer relationships remain underexplored. The authors identify a structural gap: value creation is well developed, but the financial and regulatory mechanisms for sustainable implementation are not.

A complementary systematic review of design methodologies asks a question that precedes any business model: is the right problem being solved? Most studies applied human-centered or participatory design, but focused on solution refinement and usability testing rather than early-stage problem discovery, rarely considering regulatory, data, and interoperability constraints. The authors call for an early-stage instrument linking problem discovery and evidence synthesis.

In *AI Research*, a comparative study tests whether ChatGPT, Gemini, and Copilot can detect seven types of data quality errors, from inconsistent gender labels and implausible BMI values to duplicates and date format errors. Performance varied by error type: all three models flagged extreme outliers, but none was reliable for semantic normalization, clinical plausibility checks, or missing data, and some outputs were hallucinated. LLMs can assist rapid screening, but human-in-the-loop verification and deterministic validation rules remain essential.

Under *EHR and Health Information Systems*, a scoping review from the German Virtual Reality Multidisciplinary Tumor Board (VR-MTB) project, maps tumor board practice across studies. Conventional boards are hampered by fragmented data, time pressure, and poor interoperability. Virtual boards gained traction during the COVID-19 pandemic, yet extended reality (XR) and AI tools still face integration, resource, and usability barriers despite promising pilots. Standardized processes, stakeholder engagement, and integration with hospital systems are identified as prerequisites for digital transformation.

Together, these papers trace a common thread: Digital Health innovation succeeds not through technology alone, but through careful problem framing, sustainable financial and regulatory models, trustworthy data, and seamless integration into clinical workflows.

Reflections and Perspectives on Digital Health

The two commentaries in this issue capture discussions held at DigiHealthDayS-2025, illustrating the event's role as a forum for critical reflection and exchange.

The first commentary argues that usage is not understanding: patients and citizens are too often framed as users of technology rather than as competent actors. Using the metaphor of *"the hen and the egg"*, it describes how patient- and citizen-led initiatives can close the circle from understanding data to building digital competence, integrating health, data, and digital literacy. Audience reflections revealed persistent gaps in awareness and trust despite high access and usage, positioning digital literacy as a shared societal responsibility.

The second commentary reports on the panel *"Generative AI in the Clinic – Hype, Hope, and Reality"*, where four experts in medical innovation, patient advocacy, regulation, and academic evidence examined the actual state of generative AI in medical practice, separating realistic expectations from inflated claims.

Together, these commentaries remind us that the success of Digital Health depends as much on people as on technology: on the literacy and trust of patients and citizens, and on a sober, evidence-based assessment of what new tools such as generative AI can and cannot yet deliver.

As this special issue illustrates, DigiHealthDayS-2025 was once again not only a celebration of ideas but also a platform for action. We extend our sincere gratitude to our sponsors, partners, and the vibrant DigiHealthDay community for their support. Looking ahead, we remain inspired by the vision that drives DigiHealthDay, that is, to create a Digital Health future that is smarter, fairer, and more human-centered.

Prof. Dr. Dipak Kalra, International Chair of DigiHealthDayS
Prof. Dr. Horst Kunhardt, Scientific Chair of DigiHealthDayS
Prof. Dr. Georgi Chaltikyan, Organizing Committee Chair of DigiHealthDayS
Prof. Dr. Ozar Mintser, Editor-in-Chief of Ukrainian Journal of Medical Informatics and Engineering
Dr. Fara Aninha Fernandes, Associate Guest Editor

Business Models for Digital Health Solutions: A Bibliometric and Systematic Review of Financial, Regulatory, and Adoption Dimensions

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ABSTRACT

Digital health solutions (DHSs) have significant potential to improve the efficiency, accessibility, and patient-centeredness of healthcare delivery. However, many initiatives fail to progress beyond the pilot stage due to the absence of sustainable business models (BMs) that ensure financial, regulatory, and operational viability. This study combines bibliometric analysis with a systematic review of 34 peer-reviewed articles published between 2020 and 2025 to examine how DHS BMs are structured and to identify key gaps in the literature. The bibliometric analysis reveals a shift in research focus from foundational technologies such as telemedicine and personalized medicine toward strategic dimensions, including business models, value creation, data privacy, and healthcare policy, indicating a maturing research field. Nevertheless, reimbursement remains comparatively underexplored despite its practical importance. The systematic review shows that value proposition, resources, and partnerships are the most frequently addressed business model components, whereas cost structure, licensing, customer feedback, and customer relationships receive significantly less attention. This imbalance limits the scalability and long-term sustainability of DHS initiatives. Overall, the findings highlight a structural gap in current DHS BM research, where value creation is well developed but the financial and regulatory mechanisms required for sustainable implementation remain insufficiently addressed. These insights guide researchers, policymakers, and practitioners in advancing more balanced and sustainable digital health business models.

KEYWORDS

Digital health solution (DHS), business model (BM), bibliometric analysis, systematic review, healthcare innovation

1. Introduction

Digital health solutions (DHSs) are transforming healthcare using technology, leading to improved patient care [1], and have the potential to improve the health and well-being of individuals and communities [2–4]. To fully unlock the potential of DHSs, having a clear and sustainable BM is essential [5]. A BM defines an organization's value logic, detailing how it creates and captures customer value. It is represented by an interrelated set of elements encompassing the customer, value proposition, organizational architecture, and economic dimensions [6, 7]. These elements provide a strategic framework that helps organizations navigate market complexity, adapt to an evolving business environment, and sustain long-term competitive advantage [8–10]. Lack of established sustainable and innovative BMs limits the development and successful commercialization of DHSs [5, 11].

Research Goal and Questions

This study employs a combined approach of bibliometric analysis [12, 13] and a systematic literature review [14–16] to examine the current landscape of BMs in DHS. The aim is to identify limitations, uncover key gaps in existing knowledge, and highlight essential components of BM frameworks to address the following questions and inform future research on the development and scaling of DHSs.

1. How do current DHS BMs manage financial sustainability and stakeholder alignment through cost control, revenue generation, and incentive structures?
2. How do current DHS BMs address regulatory frameworks and requirements, including medical device classification and compliance obligations?
3. How do current DHS BMs overcome adoption barriers in a dynamic healthcare ecosystem?

The remainder of this paper is structured as follows. The next section outlines the bibliometric analysis and systematic literature review methodology. The Results section presents findings organized around financial sustainability and stakeholder alignment, regulatory frameworks, and adoption barriers. The Discussion addresses limitations and gaps in the current literature, and the paper concludes with key insights and directions for future research.

2. Materials and Methods

2.1 Systematic Review

This study followed a three-phase selection process including identification, screening, and eligibility, consistent with PRISMA 2020 reporting guidelines [14], to narrow the initial pool of records to those most relevant to BMs in digital health.

In the identification phase (Figure 1), records were retrieved from five databases such as Scopus, PubMed, Web of Science, IEEE, and Google Scholar using the following Boolean search string: ("business model"*) AND ("hospital"*) AND ("digital health"*) AND (("value-based care"*) OR ("adoption"*) OR ("financial performance) OR ("data privacy"*) OR ("healthcare compliance"*)). This query returned 19,649 records, distributed across databases as shown in Table 1.

Database	Number of Records
Scopus	484
PubMed	217
Web of Science	112
IEEE	127
Google Scholar	19,300
Total	**19,649**

Table 1: Search results by database.

The second phase, known as the screening phase in Figure 1, involved filtering the identified articles based on certain inclusion and exclusion criteria. The following inclusion and exclusion criteria were applied, as shown in Table 2. Applying these criteria resulted in the removal of 4,892 records. A further refinement of the search query, restricting results to titles and abstracts, reduced the dataset to 1,249 records. The extracted articles were stored as a comma-separated values (CSV) file. After eliminating duplicates (n = 107), 1,142 records remained. Research review records (n = 77) were subsequently excluded, leaving 1,065 records for further screening.

Inclusion	Exclusion
Published in journal	Published before 2020
Reported in English	Research review
Published on or after 1st January 2020 and before the date of research, 1st March 2025.	Reported as conference papers, commentaries, theoretical papers, dissertations, book chapters, or editorials.

Table 2: Inclusion and exclusion criteria

In the final step, which includes a detailed review of the articles for relevance and quality. During this phase, the titles and abstracts of the remaining articles were evaluated to ensure they met the study's objectives. Articles that were not directly relevant were excluded. After this step, the final set of articles for inclusion in the study totaled 34, as shown in the "Included" section of Figure 1.

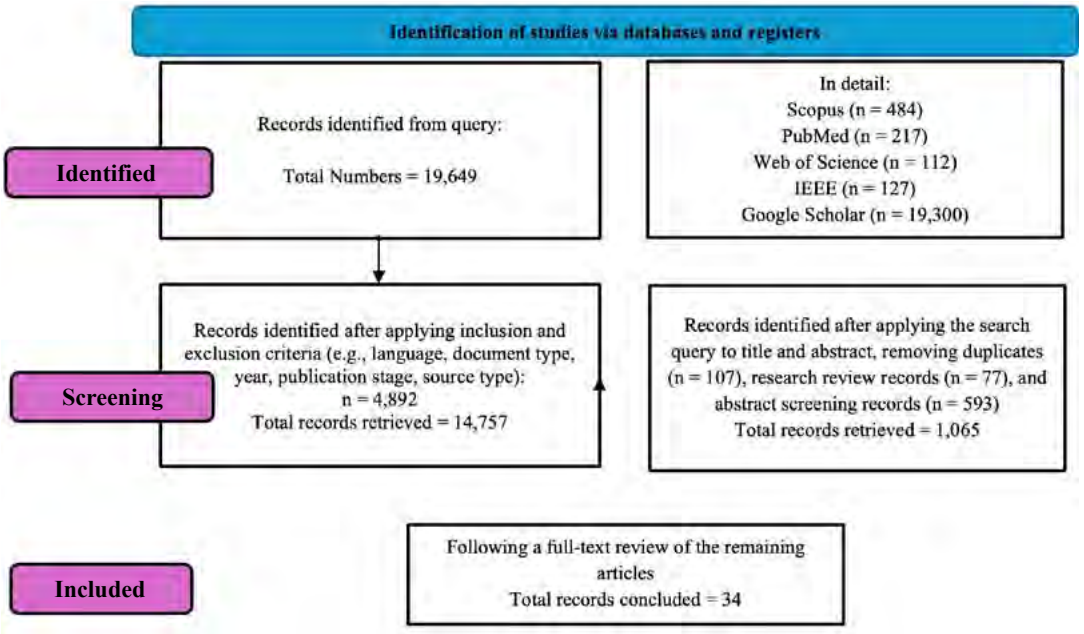


Figure 1: PRISMA flow diagram showing the study selection process.

2.2 Bibliometric Analysis

VOSviewer (version 1.6.20), developed by Leiden University [17], was used to construct and analyze the bibliometric network, including a keyword co-occurrence map and a keyword density map [12, 13]. To illustrate macro-level applications of BM research in DHS, keywords from article titles and abstracts were mapped as a co-occurrence network (Figure 2), and a separate map was generated for author keywords (Figure 3). In both maps, circle size reflects keyword frequency and distance between circles reflects co-occurrence strength; a minimum keyword frequency threshold of 3 was applied to ensure

relevance and clarity. A density visualization (Figure 4) was also produced, where point density reflects the number and weight of neighboring items, and a timeline visualization (Figure 5) shows keyword color as average year of publication, enabling identification of emerging trends within the DHS BM landscape [12, 13, 17].

3. Results

3.1 Systematic Literature Review Findings

The reviewed literature encompasses diverse range of methodologies, including qualitive research such as case studies and interview based research [5, 18–30], mixed-methods research [31], and conceptual or theoretical analyses [18, 32, 33]. These studies collectively provide insights into how BMs are structured, adapted, and implemented across various DHS contexts. Some focus on defining core BM components [26, 28, 29], as illustrated in Table 3, while others examine how external pressures such as regulation [21, 32] or innovation barriers [19, 23] influence BM design and implementation.

Several contributions explore how BMs generate value through DHSs (e.g., blockchain, AI, remote monitoring), highlighting both opportunities and structural challenges [18, 33–35]. Others propose refinements or novel BM designs to meet evolving healthcare demands [24, 27, 31, 36]. Christie et al. [19, 20] focus on implementation strategies, integrating BM components with contextual organizational insights to enhance adoption and sustainability. Fürstenau et al. [22] propose a multi-sided platform to improve personalized care and leverage real-world data. Similarly, Tekkis et al. [36] address the integration of 3D printing technology within the NHS, noting organizational and physical constraints that future BMs must overcome. Lokman et al. [25] and Saheb [31], explore telehealth and social enterprise models, highlighting pricing strategies like flat rates, subscriptions, and cross-subsidization.

Across these studies, there is a clear trend toward multi-component BMs [22, 25, 29] and ecosystem-driven BMs emphasizing stakeholder collaboration [21, 33, 35], digital infrastructure [18, 32, 36], and adaptive governance [21, 35]. However, common limitations such as small sample sizes [29], geographic constraints [26], and a predominance of qualitative or secondary data [22, 23] suggest the need for more rigorous, longitudinal, and multi-contextual studies. Table 3 illustrates the most commonly recurring components of BMs in DHS, as identified in recent studies that focus on developing or enhancing BMs in this field [19–22, 24–26, 29–31, 33, 36] .

Model components / Publication	Value proposition	Value creation	Partnetwork	Service channel	Resources	Delivery	Governance	Key activities	Cost structure	Customer relationships	Feedback	licenses	Customer segments	Provider	channel	Revenue
Viswanadham, 2021 [33]	×	×	×	×	×	×	×									
Essen et al., 2022 [21]	×	×	×	×	×	×	×									
Christie et al., 2020 [19]	×		×		×			×	×	×					×	×
Vimarlund et al.,2021 [30]	×	×	×							×			×			
Hongdao et al., 2022 [24]	×				×			×	×				×		×	
Saheb, 2020 [31]	×	×	×		×			×			×	×	×			×
Christie et al., 2021 [20]	×		×		×			×	×	×			×		×	×
Lokman et al., 2021 [25]									×		×					×
Fürstenau et al., 2021 [22]	×	×				×		×					×			
Velayati et al., 2021b [29]	×	×	×		×			×			×	×	×			×
Lupiáñez-Villanueva et al., 2020 [26]					×									×	×	×
Tekkis et al., 2022 [36]	×															
Sum	10	6	7	2	8	3	2	6	4	3	3	2	6	1	4	6

Table 3: Overview of key BM components in selected publications

As shown in Table 3, the most emphasized BM element for DHSs is the value proposition [19–22, 24, 29–31, 33, 36]. Value proposition plays a crucial role in defining BM and differentiating between various types of models [24]. A value proposition explains why customers should choose a company's products or services over competitors [21]. A strong value proposition could highlight unique features and benefits that provide additional value to customers [37, 38] and solve a customer problem or satisfy a customer need differently [39]. A well-crafted value proposition not only sets a business apart from its competitors but also captures the desires and preferences of consumers [38].

Resources, the second most frequently mentioned component [19–21, 24, 29–31, 33], refer to the essential assets such as physical assets (buildings, vehicles, equipment), financial assets, intellectual assets (brands, copyrights, patents, customer databases), and human resources, which determine the success of BM operations [38, 39]. Among these, intellectual resources are particularly critical as they are difficult to replicate [31, 38].

Partnership, as a help to an organization's operation [38, 39], is mentioned as another prominent component [19–21, 29–31, 33]. Partnerships have become important for cost savings [38], risk reduction [38, 39], acquiring resources [38, 39], and gaining knowledge [38].

Some components appeared the same number of times such as value creation [21, 22, 29–31, 33], revenue models [19, 20, 25, 26, 29, 31], customer segments [22, 24–26, 29–31] , and key activities [19, 20, 22, 24–26, 29–31]. Value creation outlines how the platform delivers on its promises [21]. Revenue represents how organizations generate income from specific customer segments, forming the foundation of business sustainability [38, 39]. Additionally, understanding different market and customer segments is crucial. It refers to the groups of individuals or entities that utilize an organization's products or services and generate revenue for the organization [38, 39]. Key activities determine the success of a BM [38, 39] by playing a crucial role in realizing the value proposition [38].

Finally, provider [26], governance, service chain [21, 33], licenses and permissions [29, 31] were among the least frequently mentioned components. Building on the identified BM components, the following thematic analysis explores how prior research has addressed critical dimensions of DHS BM.

Financial Sustainability and Stakeholder Engagement in DHS BM

Financial sustainability requires coordinating cost efficiency, rather than merely reducing costs [27]. Cost structure is a key component of DHS BMs [20], encompassing the expenses incurred by the business, including resource acquisition, regulatory compliance, clinical validation, workforce training, and hosting costs [19, 28, 40]. Reported cost structure strategies include combining grants with subscription-based models, fixed pricing with grants, fixed-cost models funded by caregivers or organizations, and research-project funding [20]. Stakeholder engagement is integral to these financial strategies, as BMs must address the needs of diverse actors, including healthcare providers, insurers, patients, and regulators [28]. Furthermore, shareholder support may be strengthened when digital transformation is perceived as enhancing financial performance [35]. A notable example of shareholder alignment is the "win–win" BM proposed by Ilan [41], in which pharmaceutical companies share revenues while insurers capture cost savings, aligning the incentives of patients, clinicians, insurers, and manufacturers to improve health outcomes while reducing systemic costs.

Revenue models present a related challenge, particularly pricing [16], which is a key component of the revenue model [16, 33]. Pricing strategies should balance affordability, market competition, and production costs to remain viable [16, 33]. Recommended pricing mechanisms include pay-as-you-go, subscription, buffet-model, and micropayment approaches [16, 42]. Some BMs also advocate tailoring revenue structures to country-specific conditions, such as self-payment, insurer reimbursement, and individual insurance schemes. Accordingly, start-ups are encouraged to align their revenue models with national health policies and reimbursement systems to support long-term viability and scalability [5].

Regulatory Frameworks and their Requirements in DHS BM

The healthcare sector is classified as highly regulated [21]. Regulatory considerations are a foundational component in the architecture of DHS BMs [5], and businesses can be positively or negatively affected by regulation and policy [43]. The absence of relevant standards, licenses, and related policies constitutes a legal barrier for DHS [16, 34], alongside barriers such as the need to prove value, secure partners, and educate the wider ecosystem [43]. Regulatory gaps can impact market entry, causing delays in the launch period and the adoption of innovations [21, 27, 43]. Since no dedicated regulatory class exists for DHS, outdated frameworks are often applied [44]; however, compliance has in some cases driven regulatory reform, as seen in Sweden [21]. Consequently, regulatory frameworks shape DHS BMs by influencing classification, compliance complexity, and market readiness, requiring organizations to balance innovation with regulatory adaptability.

Adoption Barriers in DHS BM

Despite the growing use of DHS, adoption challenges persist [45] at the human, social, and organizational levels [27, 46]. DHS adoption has not yet reached scale, although COVID-19 accelerated uptake through shifts in funding models and reduced reliance on in-person contact [23, 27]. Likewise, technologies with reputational benefits, such as 3D printing, continue to face adoption barriers [36]. Reported barriers include data security concerns [23, 26, 31], ease of use and access to technology [31, 47], regulation [33, 48], age [27], revenue, recommendation, and provider models [26], psychological factors such as technology anxiety, health consciousness, hedonic motivations, and habits [31], and cultural differences [27]. Inadequate implementation strategies and atheoretical deployments further hinder scaling [19], although increasing adoption among patients and healthcare professionals can strengthen the sociopolitical legitimacy of DHS [21].

Adoption can be strengthened through the development of digital complementary assets, such as hospital-based technological expertise, which often has a greater influence than the regulatory environment itself [48]. Additional enablers include clear evaluation and reimbursement strategies [23], public funding structures [27], future pricing models [19], and the integration of big data and social media [31]. A strong business case is also a direct driver of adoption [27]. Furthermore, strategic positioning and governance aligned with policy and stakeholder expectations can help build legitimacy by clarifying the value of DHS to employers, clinicians, and patients, although these approaches do not replace formal validation [43]. DHS adoption typically follows an S-curve, beginning slowly before accelerating as the technology matures [33].

3.2 Bibliometric Analysis Results

Figure 2 presents the co-occurrence network of 124 (of 647) high-frequency title and abstract keywords, organized into four thematic clusters. Cluster I (red) includes artificial intelligence (AI), adoption, communication, COVID-19, data privacy, decision making, digital health, healthcare, healthcare policy, human, medical information, public sector, and reflects a strong focus on the adoption and regulation of digital technologies, particularly AI in public health, especially in response to the COVID-19 pandemic. The inclusion of human and medical information further underscores ethical considerations such as data privacy and the responsible management of digital health information. Cluster II (green) includes article, big data, qualitative research (with a focus on demographic features like gender), risk assessment, work experience, patient engagement, marketing, and social media, reflecting patient-centered care, market research, and social behavior in the context of digital health, pointing to empirical studies of adoption dynamics. Cluster III (blue) includes healthcare cost, healthcare delivery, health plan implementation, incentive, investment, stakeholder, and telemedicine centers on the financial and organizational dimensions of DHS delivery. Terms like healthcare cost, health plan implementation, and investment highlight financial strategies that directly influence stakeholders' willingness to adopt telemedicine and invest in related technologies, speaking to RQ1's focus on cost control, revenue, and incentive structures. Cluster IV (yellow) includes business model, digital transformation, dynamic capability, sustainability, and value creation, emphasizing strategic transformation within healthcare and related industries through digital technologies. Also, a separate map was generated for author keywords, where 37 out of 297 keywords met the inclusion threshold, as illustrated in Figure 3.



Figure 2: Network visualization map of co-occurrence - title and abstract keywords.

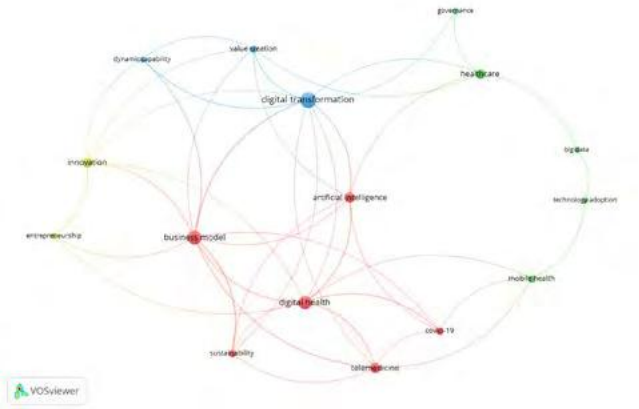


Figure 3: Network visualization map of co-occurrence – author keywords.

We created a density visualization of the high-frequency keywords, as shown in Figure 4, where the density of each point is influenced by the number of neighboring items and their respective weights. The more items that surround a point, and the higher their weights, the more yellow the point appears [49]. At the center of the map, the terms "human," "article," and "telemedicine" appear with the highest density (in yellow), indicating their central role in the research landscape and their pivotal contribution to knowledge production within the field. On the right side of the map, "business model" and "digital transformation" also show relatively high density, underscoring their importance in the related literature. Other keywords such as "healthcare delivery," "digital health," "artificial intelligence," "healthcare," and "gender" appear with moderate density, reflecting their notable but comparatively lesser presence in the research body. Towards the periphery of the map, keywords appear in shades of blue, suggesting that while these concepts are part of the overall network, their frequency and influence are relatively lower compared to the core terms. This analysis helps researchers identify both prominent and underexplored areas within the DHS domain, providing valuable guidance for more targeted and impactful future research and development.

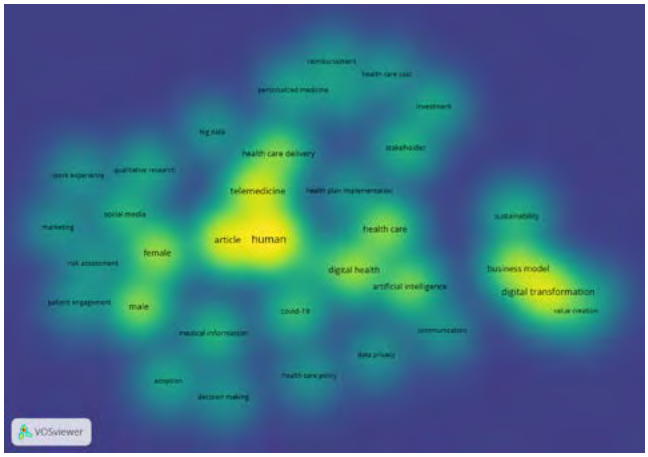


Figure 4: Density visualization map of co-occurrence - title and abstract keywords.

Figure 5 presents a timeline-based visualization of prominent keywords, where the color of each circle represents the average publication year of the associated term, the lighter the color, the more recent the keyword [49]. This visualization enables researchers to trace the evolution of high-frequency keywords over time and identify emerging trends within the DHS business model (BM) landscape. The figure reveals that topics such as digital transformation, digital health, AI, BM, stakeholder, sustainability, adoption, data privacy, value creation, patient engagement, and healthcare policy have garnered significant, sustained research attention, particularly from 2022 onward, as these nodes are colored in shades of light green to yellow. There is also a noticeable rise in interest around 2022 in keywords like healthcare delivery, marketing, big data, work experience, and social media, reflecting a growing emphasis on the communication and implementation strategies of DHS during that period. In contrast, nodes colored in purple and blue reimbursement, personalized medicine, health plan implementation, telemedicine, risk assessment, human, and public sector suggest these themes were more central to earlier studies, primarily those published in 2021 or earlier, forming the foundational basis of DHS research. This temporal mapping illustrates the field's evolutionary trajectory between 2020 and 2025: earlier work centered on foundational technologies such as telemedicine and personalized medicine, while more recent research has shifted toward strategic and systemic concerns, including the implementation of digital technologies through BMs, cost structures, value creation, and policy frameworks, signaling a maturing DHS research landscape.

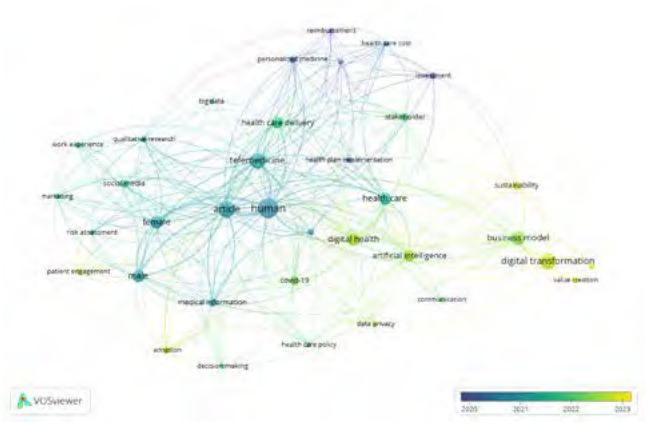


Figure 5: Visualization map of the evolution of keyword frequency over time - title and abstract keywords.

These macro-level bibliometric patterns broadly corroborate the thematic findings from the systematic review (Section 3), while also highlighting reimbursement as a comparatively under-researched term compared with its regulatory and financial aspects.

Discussion

The findings highlight the importance of BM structure in the implementation of DHS. The strong emphasis on value proposition aligns with the need to justify the utility and relevance of innovations to stakeholders and end-users. Similarly, resources (e.g., funding, infrastructure, expertise) and partnerships between organizations (including providers, regulators, and insurers) are recognized as two key components enabling the effective delivery of DHS.

However, limited attention to components such as cost structure, licensing, and feedback suggests a missed opportunity to align implementation strategies with scalable and sustainable BMs. These overlooked elements are critical for long-term viability, shaping not only how innovations are financed and governed but also how they evolve in response to user needs, regulatory change, and market dynamics. Cost structure, including pricing mechanisms, expenses, and revenue model, is crucial for ensuring DHS remains financially viable and creates value for both providers and users as they scale. Licensing plays a critical role in ensuring regulatory compliance and facilitating broader dissemination across regions and systems, and can also provide a competitive advantage; however, the lack of clear regulations specific to DHS, combined with high licensing costs, remains a significant barrier. Feedback mechanisms and customer relationships, though mentioned in only a few articles, not only improve the functionality and responsiveness of DHS but also foster user engagement and trust, thereby promoting greater adoption and sustained use.

The bibliometric analysis reveals a strong focus on telemedicine, humans, digital transformation, and BMs, underscoring their pivotal roles in the existing literature. However, there is comparatively less emphasis on the value DHS creates, its adoption barriers and solutions, related policies, costs, or reimbursement issues. Timeline visualizations show an evolution from foundational topics such as telemedicine and human factors toward a more recent focus on strategic themes, including BMs, sustainability, adoption, value creation, data privacy, and healthcare policy.

This uneven emphasis raises concerns about whether current research fully addresses the complete range of BM components, particularly given that DHS must be integrated into complex, resource-constrained health systems. Despite meaningful progress, strengthening BMs for DHS will require deliberate attention to the underexplored components identified above, including cost structure, licensing, and feedback mechanisms, alongside the broader financial, regulatory, and adoption-related conditions examined throughout this review.

Limitations

This review has several limitations that should be considered when interpreting its findings. First, the temporal scope was restricted to studies published between 2020 and March 1, 2025; earlier foundational work and the most recent developments in this fast-moving field may therefore be underrepresented. Second, the final sample of 34 articles, while consistent with the review's inclusion criteria, is relatively small and may be concentrated in a subset of national and organizational contexts, which could limit the generalizability of the identified BM patterns. Finally, the bibliometric analysis relies on keyword co-occurrence within a single Boolean search string; studies describing similar phenomena using different terminology (e.g., "digital health technology," "eHealth," "mHealth") may not have been captured, and the minimum keyword-frequency threshold of 3 may have excluded low-frequency but conceptually important themes.

Conclusion

This review set out to examine how current BMs DHSs manage financial sustainability and stakeholder alignment, navigate regulatory frameworks and requirements, and overcome adoption barriers in a dynamic healthcare ecosystem. Across the 34 reviewed studies, financial sustainability remains constrained by an over-reliance on limited revenue models and underdeveloped cost structures, despite their centrality to long-term viability; where stakeholder alignment is addressed, it is largely framed around collaborative arrangements between providers, insurers, and technology developers. Regulatory frameworks, particularly medical device classification and compliance obligations, shape which BM archetypes are viable in practice, and while compliance is costly, it can also drive legitimacy and market access when navigated proactively. Adoption barriers persist at technological, organizational, and behavioral levels and are most directly addressed through BM components such as value proposition, customer relationships, and feedback mechanisms, which remain comparatively underexplored in the literature. Taken together, these findings indicate that BM research on digital health has matured in describing structural components but has not yet adequately connected those components to the financial, regulatory, and behavioral conditions needed for DHS to scale sustainably. As an ageing society presents both a major challenge and a significant market opportunity, closing this gap is essential for turning promising digital health innovations into durable, adopted solutions.

Building on these findings, future research should proceed in four directions. First, more rigorous cost estimation and assessment of the financial and societal benefits of DHS are needed to offer researchers, policymakers, service providers, and industry stakeholders a clearer basis for investment and adoption decisions. Second, given the dynamic and uncertain nature of this field, future work should examine how platform-based and hybrid digital-physical BMs can adapt to evolving regulatory and reimbursement environments [34], including which BM components are most sensitive to regulatory change and how these can be optimized for resilience. Third, greater attention should be paid to the BM components that most directly shape adoption, such as value proposition, customer relationships, feedback mechanisms, and delivery channels, as these drive user engagement, trust, and long-term use. Finally, future studies should more directly integrate patient perspectives into BM design [28], ensuring that efforts to scale and sustain DHS in dynamic healthcare environments remain grounded in end-user needs alongside financial and regulatory considerations.

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Bridging Gaps in Healthcare Innovation: A Systematic Review of Design Methodologies for Problem Discovery in Technological Health Products

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ABSTRACT

Digital health and medical technology products are often developed with strong technical expertise but shallow early problem framing. This can lead to misaligned solutions, rework, and low adoption in real-world care. This systematic review synthesizes how design methodologies are used to deepen problem understanding during the creation of technological healthcare products.

We followed PRISMA 2020 guidance and structured the protocol using PICOC. We searched PubMed, Scopus, ScienceDirect, and BVSalud for peer-reviewed articles in English published from 2016 onward that described frameworks or methodological processes for developing technological health products. A nine-item quality checklist assessed how clearly studies reported procedures, objectives, structures, challenges, limitations, and multidisciplinary collaboration.

The search identified 513 records; 33 full texts were screened, and 11 studies met the inclusion criteria. Most used a human-centered, user-centered, or participatory design to support the development of medical devices, monitoring systems, digital mental health services, reproductive health platforms, and tools for older adults and children. Design methods were widely applied to improve usability, acceptability, and experience, and to address the needs of specific populations. However, most frameworks focused on solution refinement and usability testing rather than deep, systematic early-stage problem discovery, and regulatory, data, and interoperability constraints were rarely integrated in the initial design phases.

The review indicates that design methodologies play an important role in the included health innovation literature but also reveals a gap: there is no consolidated, early-stage instrument that links problem discovery, evidence synthesis, and explicit go/hold/no-go decisions for technological health products.

KEYWORDS

Health, innovation, human-centered design, digital health, product development, systematic review

1. Introduction

Digital health and medical technology innovation has expanded rapidly in recent years. New devices, digital platforms, remote monitoring systems, and digitally enabled service models promise better diagnosis, coordination, and care delivery. However, many innovations do not progress successfully from promising concepts to sustainable implementation in real-world health settings. Common reasons include poor usability, limited fit with professional workflows, insufficient attention to patient experience, low compatibility with organizational routines, and the late recognition of regulatory, data, and interoperability constraints.

Design methodologies have been widely proposed as a way to reduce these risks. Human-centered design (HCD), user-centered design (UCD), participatory design, co-design, challenge-based learning, and early health technology assessment all offer structured ways to understand users, contexts, unmet needs, and implementation constraints before substantial development effort is invested. In health settings, these approaches are often intended to improve usability, strengthen relevance to target populations, increase stakeholder engagement, and reduce the gap between technical innovation and everyday care practice. Studies in connected health, remote monitoring, children's mental health, reproductive health platforms, and technologies for older adults suggest that such approaches can support better requirement elicitation, more acceptable interfaces, and stronger alignment with user needs.

At the same time, the literature also shows that these methodologies are not easy to apply consistently. Human-centered and participatory approaches can be resource-intensive, rely on multidisciplinary coordination, and produce findings that are difficult to translate into explicit decision criteria. In addition, there is often a gap between the general promise of design methods and their operational use in early health innovation. Some studies emphasize co-design and usability improvement, while others focus on implementation, device selection, or workflow fit. As a result, the field contains many relevant methodological contributions, but fewer syntheses of how these approaches are actually being used during early-stage problem discovery in technological healthcare development.

From a design studies perspective, this gap is important. Classic design literature argues that innovation depends not only on generating solutions, but on carefully framing and reframing problems, engaging stakeholders, and moving iteratively between problem and solution spaces [1–5]. In healthcare, this logic is especially relevant because poorly framed problems may lead to technically functional products that fail in practice due to workflow mismatch, implementation barriers, or weak adoption. Related traditions in human factors and implementation research further suggest that work systems, contextual conditions, and organizational compatibility should be considered early, not only after design decisions have already been made.

Despite this, there is still limited synthesis of how design methodologies are used specifically to deepen problem understanding before or during the earliest stages of technological health product development. Existing papers often focus on a specific intervention, population, or design process, but less often examine the broader methodological picture: which procedures are being used, what benefits they are intended to offer, how standard frameworks are operationalized, what barriers arise in practice, and where gaps remain.

This systematic review addresses that need. The review was structured using PICOC because the topic is not primarily about comparing interventions, but about identifying and synthesizing methodological approaches used in a defined population and context. The population was health innovators and scientific entrepreneurs involved in technological healthcare development; the intervention was the use of frameworks or structured methods to deepen problem understanding; comparison was not applicable; the outcomes concerned methodological procedures, objectives, reported benefits, limitations, and challenges; and the context was healthcare, broadly defined. This structure was intended to support a review that is methodologically transparent while remaining broad enough to capture heterogeneous design-related literature.

By synthesizing how design methodologies are used in early health innovation, this review aims to clarify current practice, identify methodological strengths and weaknesses, and support the development of more explicit early-stage discovery approaches for technological health products.

2. Methods

2.1 Review Design

The review followed the logic of the PRISMA 2020 statement for systematic reviews [6]. The protocol was structured using PICOC (Population, Intervention, Comparison, Outcome, Context) to make inclusion criteria explicit.

The protocol was not registered in a public registry. The review is based on the methodological chapter of a Master's thesis focused on early-stage health innovation.

2.2 PICOC Protocol

Population: Health innovators and scientific entrepreneurs involved in developing technological healthcare products (for example: medical devices, digital platforms, and connected health services).

Intervention: Use of frameworks, methodologies, or structured processes that deepen problem understanding in the development of technological health products (for example: HCD, UCD, participatory design, or design frameworks focused on needs analysis).

Comparison: Not applicable. Studies were not required to compare design versus non-design approaches.

Outcome: Description and assessment of methodological processes, including procedures, stages, and tools used for problem discovery, user needs analysis, requirements definition, and risk identification.

Context: No restriction regarding care setting or country. Studies could take place in hospitals, community health, educational, or home environments.

2.3 Research Questions

The review addressed four research questions:

1. What methodological procedures are used during the creation of healthcare products?
2. What are the objectives of using product design in the healthcare domain?
3. Is the use of standard frameworks common in the creation of technological healthcare products?
4. What challenges are reported in the development of health technology products?

These questions guided both study selection and thematic synthesis.

2.4 Search Strategy

A structured search strategy was developed to combine terms related to design methodologies, health, problem exploration, and development processes.

The core search logic used the following terms: ("framework" OR "methodology") AND ("health" OR "healthcare") AND ("problem" OR "root cause" OR "need" OR "necessity") AND ("product design" OR "product development"). Small adaptations were made to accommodate the syntax of each database, including the use of controlled vocabulary where appropriate.

The intention of this strategy was to identify studies that explicitly described structured methodological approaches for understanding problems and guiding the development of healthcare technologies. At the same time, the search strategy was relatively narrow and emphasized explicit methodological language. It did not systematically include additional terms such as “digital,” “technology,” “technological,” “innovation,” “co-design,” or “participatory design,” nor did it intentionally broaden the search toward earlier pre-product innovation phases that might not yet be described using product development terminology. This decision likely increased precision but may have reduced recall. To ensure transparency, this limitation is revisited in the Discussion and Limitations sections.

2.5 Information Sources

Four databases were searched:

- PubMed
- ScienceDirect
- Scopus
- BVSalud (BVS/Virtual Health Library)

The search covered publications from January 2016 onwards, reflecting the growth of digital health and design methods in recent years. The last search update for the thesis was in 2023. Only articles in English were considered.

2.6 Eligibility Criteria

Inclusion Criteria:

- Peer-reviewed articles that describe methodological procedures for creating technological healthcare products (devices, software, platforms, or service innovations with a technological component).
- Studies that present structures, frameworks, or stepwise processes for deepening problem understanding (for example: needs analysis, contextual research, participatory design, or structured requirements gathering).
- Articles that report applications in healthcare or health-related wellbeing contexts.

Exclusion criteria:

- Duplicate records
- Grey literature (reports, theses, conference abstracts without full papers)
- Short articles or editorials with insufficient methodological detail
- Studies not written in English
- Studies outside the scope (for example, design frameworks not applied to health)
- Studies published before 2016

2.7 Study Selection

All records retrieved from the databases were exported, and duplicates were removed. Titles and abstracts were screened against the inclusion criteria. Potentially relevant articles were read in full. Reasons for exclusion at the full-text stage included lack of explicit methodological description, focus on purely clinical efficacy without design procedures, and absence of a technological product component.

The search returned 513 records. After removing duplicates and screening titles and abstracts, 33 articles remained for full-text assessment. Applying the inclusion and exclusion criteria led to 11 final studies included in the qualitative synthesis. The study selection process is summarized in Figure 1.

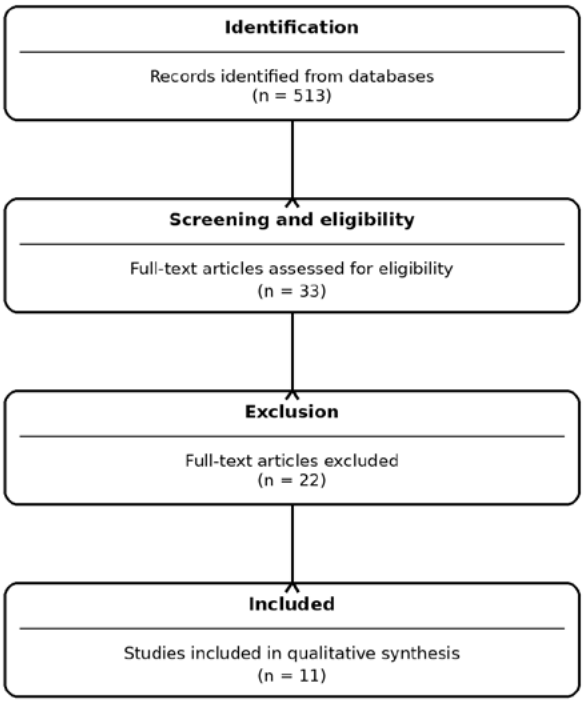


Figure 1: PRISMA flow diagram of study selection.

2.8 Quality Appraisal

A nine-item checklist was used to assess the clarity and completeness of methodological reporting in each included study. Each item was rated as Yes, Partially, or No. The checklist examined whether the study: (1) identified and analyzed methodological procedures used in the creation of healthcare products; (2) presented objectives achieved through product design; (3) provided evidence of the use of generic frameworks; (4) described challenges in developing health technology products; (5) presented a clearly described structure for building a healthcare product; (6) highlighted stages or steps used in creating the product; (7) described limitations encountered during development; (8) clearly related design methodologies to the creation of healthcare products; and (9) adopted a multidisciplinary approach.

The checklist was used descriptively rather than as a basis for excluding studies. Its purpose was to support a structured synthesis of how well the literature reported not only methods and intentions, but also process detail, implementation relevance, limitations, and interdisciplinary characteristics.

2.9 Data Extraction and Synthesis

For each included study, data were extracted on citation details, product or innovation type, target population and context, design methodology or framework used, discovery and development procedures, intended objectives, reported benefits or useful outputs from the design process, structure and stages of development, use of generic or adapted frameworks, reported challenges, stated limitations, and evidence of multidisciplinary collaboration.

To align the synthesis with the quality appraisal logic, the Results section was organized around the same analytical dimensions assessed in the checklist: methodological procedures; objectives and reported benefits; framework use; structure and stages; challenges and limitations; and multidisciplinary collaboration. A thematic synthesis was then developed across studies to identify recurring patterns and cross-cutting gaps.

3. Results

3.1 Overview of Included Studies

The 11 included studies span a diverse set of health innovation contexts, but several clusters are visible. Medical device development and early health technology assessment were represented by Busch et al. [7] and Smith et al. [8], while connected health and usability-oriented digital design for older adults were represented by the two studies by Harte et al. [9, 10]. Community and implementation-focused design was represented by Adam et al. [11], and youth-oriented national digital platform development by Ippoliti et al. [12]. Older adult needs were also addressed through interdisciplinary product design work in Chile [13], while broader conceptual work on design and well-being was represented by Kafaee et al. [14]. Device selection methodology for remote health programs was addressed by Polhemus et al. [15], and child-focused service or technology design by Lyon et al. [16] and Sims [17].

Across the included sample, most studies used qualitative or mixed approaches and relied on interviews, observations, workshops, co-design activities, prototype evaluation, or systematic synthesis. Although the studies varied in product type, target population, and reporting depth, they collectively show that design methodologies in health are being used across device, platform, service, and implementation settings rather than in only one narrow domain. Key characteristics of the 11 included studies are summarized in Table 1.

Table 1: Characteristics of the 11 included studies on design methodologies in technological health product development

Study	Country / context	Health domain / target population	Technology / innovation type	Design methodology	Main stages / procedures	Intended objective	Reported benefits / useful outputs	Reported challenges / limitations	Multidisciplinary involvement
Busch et al. (2021)	Medical device development context; angiographic equipment	Medical devices; complex device development	Medical device innovation / angiographic equipment	Innovation and development process optimization	Analysis of the innovation and development process	Optimize the innovation and development process of medical devices	Highlights the Importance of user involvement and interdisciplinary collaboration in complex device development	Not detailed	Yes
Harte et al. (2017a)	Connected health system context	Health system users	Connected health system	Human-centered design	Three-phase methodology: use case development, usability inspections, and user testing	Improve usability, human factors, and user experience	Improved usability, human factors, and user experience	Not detailed	Yes / implied
Harte et al. (2017b)	Older adult falls risk context	Older adults	Mobile app within an integrated falls risk detection system	Human-centered design	Three-phase methodology emphasizing usability improvement	Improve usability and user experience for older adult users	Improved usability and user experience for older adult users	Not detailed	Yes / implied

Study	Country / context	Health domain / target population	Technology / innovation type	Design methodology	Main stages / procedures	Intended objective	Reported benefits / useful outputs	Reported challenges / limitations	Multidisciplinary involvement
Smith et al. (2019)	Early health technology assessment / medical device innovation	Clinicians in Medical de vice innovation	Early HTA / systematic review	Systematic review	Review of clinicians' role in early HTA	Define the clinician's role in early HTA during Medical device innovation	Identified clinician contributions in needs-driven problem solving, conformity assessment, economic evaluation, and conflicts of interest	Not detailed	Yes / partial
Adam et al. (2020)	Complex health systems / community health volunteer context	Community health volunteers	Human-centered design applied to implementation in health systems	Theory-driven human-centered design	Integration of HCD with theoretical frameworks	Sustain trust in complex health systems and support continued volunteer engagement	Suggests that combining HCD with theoretical frameworks can strengthen implementation capacity and sustained engagement	Implementation challenges in complex health systems are central to the study	Yes / partial
Ippoliti et al. (2021)	Rwanda / national youth reproductive health platform	Rwandan youth	National digital health platform (Cyber-Rwanda)	Human-centered design	Development, launch, and evaluation with active youth involvement	Improve reproductive health for Rwandan youth and ensure usefulness and accessibility	Shows the value of active youth involvement in making the platform useful and accessible	Not detailed	Yes

Study	Country / context	Health domain / target population	Technology / innovation type	Design methodology	Main stages / procedures	Intended objective	Reported benefits / useful outputs	Reported challenges / limitations	Multidisciplinary involvement
Briede-Westermeyer et al. (2021)	Chile / Interdisci-plinary product design context	Chilean elderly	Product design for health needs of older adults	Interdisciplinary product design experience	Baseline interdisciplinary design experience	Address the health needs of the Chilean elderly through product design	Highlights the Relevance of interdisciplinary work for identifying and addressing elderly health needs	Not detailed	Yes
Kafaee et al. (2021)	Conceptual / broader technology development context	User well-being broadly defined	Technology development framework	Design for well-being	Considers well-being across technology development phases	Make well-being a primary design criterion	Supports a more holistic and user-centered view of technology development	Not detailed	Not explicit
Polhemus et al. (2020)	mHealth / remote monitoring context	Patients in mHealth programs	Device select ion framework for remote health programs	Human-centered design-based framework	Development of a framework and case study for device selection	Guide designers to consider patient experience when selecting devices	Provides a practical framework for device selection grounded in patient experience	Not detailed	Yes / partial

Study	Country / context	Health domain / target population	Technology / innovation type	Design methodology	Main stages / procedures	Intended objective	Reported benefits / useful outputs	Reported challenges / limitations	Multidisciplinary involvement
Lyon et al. (2020)	Children's mental health services context	Children	Service innovation / mental health services	Human-centered approach	Design-oriented approach to service improvement	Improve accessibility, effectiveness, and acceptance of children's mental health services	Shows how user-centered design can improve accessibility, effectiveness, and acceptance	Not detailed	Yes / partial
Sims (2018)	Children's healthcare technology design context	Children	Healthcare technology for children	Participatory design	Involvement of children from early design stages	Ensure solutions are appropriate to children's cognitive, emotional, and physical capacities	Ensures children's perspectives are considered from early design stages	Not detailed	Yes

3.2 Methodological Procedures, Structures, and Stages

Across the included studies, the most common pattern was the use of iterative human-centered or user-centered design processes, although the degree of procedural detail varied considerably. Harte et al. [9, 10] provided the clearest examples of explicit multi-phase design structures, describing sequences that moved from use case development and contextual understanding into usability inspection and user testing. Polhemus et al. [15] similarly proposed a structured framework for device selection in remote health programs, while Ippoliti et al. [12] described a development process in which platform design, launch, and evaluation were closely linked to active youth participation. In contrast, other studies, such as Busch et al. [7], Lyon et al. [16], and Kafaee et al. [14], emphasized broader process logic or design orientation rather than a tightly standardized stepwise model.

A recurring pattern across the sample was that later phases of design were described more explicitly than early-stage problem framing. Many papers clearly documented prototype refinement, usability improvement, or implementation-oriented adaptation, but fewer described in detail how they moved from a broad problem space to prioritized development directions. Even so, the sample as a whole shows that design methodologies in health are rarely confined to interface-level refinement alone. Instead, they are used to support requirement clarification, contextual understanding, and the shaping of development decisions across multiple kinds of technological health innovation.

3.3 Objectives and Reported Benefits of Design Method Use

Across the included literature, design methodologies were used for several related purposes. A central objective was to improve usability and user experience, particularly for populations such as older adults and children, as seen in the studies by Harte et al. [9, 10], Lyon et al. [16], and Sims [17]. Another objective was to improve contextual fit by grounding product or service design in the needs, experiences, and constraints of intended users, as in Ippoliti et al. [12], Adam et al. [11], and Polhemus et al. [15]. In medical device and early HTA contexts, Busch et al. [7] and Smith et al. [8] also suggest that design-related approaches can support more relevant collaboration between clinical and technical actors.

The included papers also reported useful outputs from using these methods. In the Harte studies, the design process contributed directly to improved usability and user experience. In Ippoliti et al. [12], active user involvement helped make the platform more useful and accessible to the target youth population. In Adam et al. [11], theory-driven human-centred design was linked to the capacity to address implementation challenges in complex systems, while Polhemus et al. [15] generated a practical framework for device selection based on patient experience. Busch et al. [7] emphasized the value of interdisciplinary collaboration and user involvement in complex device development, and Sims [17] highlighted the importance of ensuring that children's perspectives are incorporated from the earliest design stages. Taken together, these findings indicate that design methodologies often produce concrete intermediate benefits, even when the reporting of those benefits is uneven across studies.

3.4 Use of Generic Frameworks versus Adapted Approaches

Standard methodological families were visible across the included studies, but they were rarely applied as fixed, fully standardized protocols. Human-centered design, user-centered design, participatory design, interdisciplinary design, and design for well-being approaches were all present, yet most papers adapted these traditions to fit a specific health context rather than following one rigid framework. Harte et al. [9, 10], Ippoliti et al. [12], and Polhemus et al. [15] were among the clearest examples of studies that translated broader human-centered design principles into more explicit health innovation procedures.

This suggests partial methodological standardization rather than full uniformity. The field has recognizable design traditions and recurring procedural logics, but these are used pragmatically and selectively. That flexibility can be valuable in healthcare, where users, workflows, and implementation conditions

vary greatly. At the same time, it makes direct comparison across studies more difficult and reduces the availability of clear procedural guidance for early-stage innovators who need more than broad design principles.

3.5 Challenges, Limitations, and Underreported Areas

Several challenges recurred across the included studies. One was the difficulty of developing a sufficiently deep understanding of user needs, especially among populations such as older adults, children, and community-based participants, whose needs may be variable, tacit, or difficult to capture through conventional elicitation methods. Another was the challenge of translating promising concepts into real care settings. Adam et al. [11] explicitly addressed implementation complexity in health systems, while Polhemus et al. [15], Lyon et al. [16], and Ippoliti et al. [12] all suggest that contextual fit and sustained use cannot be assumed from design quality alone.

The review also identified important underreported areas. Explicit study limitations were not always well documented, and the earliest phases of discovery were often described less transparently than later prototyping or evaluation stages. Regulatory fit, interoperability, data governance, and other broader implementation constraints were only inconsistently incorporated into the design processes described in the included sample. This uneven reporting limits the ability to assess how transferable or robust some of the approaches may be in practice.

3.6 Multidisciplinary Collaboration and Cross-Cutting Synthesis

Multidisciplinary collaboration was one of the strongest recurring features across the included studies. Busch et al. [7], Smith et al. [8], Adam et al. [11], Briede-Westermeyer et al. [13], and Polhemus et al. [15] all point, in different ways, to the importance of bringing together clinical, technical, design, implementation, or user perspectives. In some studies, such collaboration was itself part of the design method rather than merely a background condition.

Taken together, the included literature suggests a field that is strongly committed to participatory and user-oriented work but less explicit about early-stage problem prioritization and integrated decision-making. The dominant pattern is not the absence of design methodology, but rather an uneven distribution of methodological detail across the innovation journey. Design methods are clearly being used to improve usability, contextual fit, and stakeholder alignment, yet the transition from early problem exploration to explicit development decisions is still less consistently articulated.

4. Discussion

4.1 Design Methodologies were Prominent in the Included Literature, but Early Problem Discovery was Less Fully Developed

The reviewed studies show that design methodologies were prominent across the included sample of technological health innovation papers. Human-centered, user-centered, and participatory approaches were repeatedly used to improve usability, adapt solutions to specific populations, and support collaboration across stakeholders. In that sense, the literature included in this review consistently treated design methods as relevant to the development of healthcare technologies.

At the same time, the findings suggest an imbalance in how these methodologies are operationalized. Across the included papers, later phases such as prototyping, usability testing, and refinement were usually described more clearly than the earliest phases of problem framing, prioritization, and evidence-based narrowing of scope. This does not mean that early discovery was absent, but rather that it was less systematically documented and less consistently converted into explicit decision logic.

This pattern is broadly consistent with classic design literature, which argues that innovation depends on sustained movement between the problem and solution spaces and on iterative reframing with stakeholders [1–5]. The studies reviewed here suggest that healthcare innovation often adopts the language and later-stage practices of design, but does not always describe early problem exploration with the same level of procedural clarity.

4.2 Fragmentation across the Innovation Journey

One of the clearest interpretive patterns emerging from the Results is fragmentation across the innovation journey. The reviewed studies documented valuable work on contextual inquiry, co-design, usability improvement, implementation support, device selection, and multidisciplinary collaboration, but these elements were not usually integrated into a single end-to-end discovery-to-decision structure. Instead, different studies emphasized different segments of the process.

This interpretation is grounded in the Results in three ways. First, framework use was often generic and adapted rather than standardized, which limited comparability across papers. Second, reporting was stronger for design and refinement stages than for early prioritization and problem framing. Third, contextual constraints such as interoperability, regulation, and data governance were only inconsistently incorporated into the earliest phases of development. Together, these findings suggest that the literature contains many relevant methods, but fewer integrated approaches that connect problem discovery, contextual analysis, evidence synthesis, and explicit innovation decisions.

This fragmentation matters because early-stage health innovation is rarely hindered by design quality alone. It is also shaped by feasibility, workflow compatibility, implementation conditions, and system-level constraints. When these issues are addressed in disconnected ways or only later in development, the risk of rework and misalignment increases.

4.3 Implications for Scientific Entrepreneurs and Health Innovators

For academic teams, hospital innovators, and early-stage entrepreneurs, the implications are clear.

They need structured yet lightweight tools that translate the best of HCD and early technology assessment into actionable steps. These tools should help them move from initial observations or research results to a documented evidence base that supports key decisions. They should also help teams make risks explicit early on, especially in relation to patient safety, ethics, regulatory fit, interoperability, and stakeholder adoption.

Beyond HCD, human-factors and systems-engineering frameworks such as SEIPS 2.0 and SEIPS 3.0 explicitly connect work systems, processes, and outcomes in healthcare and offer practical tools for mapping constraints and risks [18, 19]. Integrating these models with the design methods identified in this review could help teams anticipate workflow, safety, and resource issues before substantial investments are made.

Diffusion-of-innovations research also highlights attributes such as relative advantage, compatibility, and complexity as central drivers of adoption [20]. Positioning these constructs as explicit discovery questions can support more realistic go, hold, or no-go decisions for technological health products.

Finally, well-established usability-testing approaches can be used not only to evaluate solutions but also to trigger reframing of the underlying problem when tests reveal systematic misalignment with users' needs [21].

These broader methodological lenses help explain why the present review identified a gap between user-centered discovery and implementation-aware decision-making. Human-factors frameworks such as SEIPS emphasize that technologies must be understood in relation to work systems, care processes,

and safety outcomes, while diffusion-of-innovation theory highlights compatibility, complexity, and organizational fit as central to adoption. Usability-testing traditions likewise reinforce that testing should not be treated only as interface evaluation, but also as a source of evidence about whether the underlying design assumptions are sound. In this manuscript, these traditions are not treated as part of the included review sample, but as interpretive frameworks that help contextualize the findings.

4.4 Research and Practice Directions

Future work should build on the strengths of the reviewed literature while addressing its remaining fragmentation. One priority is the development of decision-oriented instruments that help innovators document the target problem, relevant stakeholders, evidence gathered, major contextual constraints, and the criteria used to decide whether to proceed, pause, or redirect development. A second priority is to examine whether stronger discovery processes actually improve downstream outcomes such as reduced rework, earlier pivots, lower development cost, or fewer delays related to implementation and regulation. A third direction is to bring implementation science and human-centered implementation frameworks into the earliest phases of design rather than treating implementation as something that happens only after a solution has already been shaped.

A further priority is broader contextual coverage. The reviewed sample already shows that design methodologies are being used across devices, digital platforms, services, and community-health settings, but more studies are needed from underrepresented contexts, including Latin America and other regions where health innovation often develops under different institutional and resource constraints. More explicit reporting of discovery stages, design decisions, and implementation-related trade-offs would also make future literature more useful for both researchers and scientific entrepreneurs.

5. Limitations

This review has several limitations that should be considered when interpreting its findings. First, the final corpus was relatively small, with 11 studies included in the qualitative synthesis. Although this number was sufficient to identify recurring methodological patterns, it limits the breadth of health domains, technologies, and design traditions represented in the review.

Second, the search strategy was deliberately focused on explicit methodological language and combined a relatively narrow set of terms related to frameworks, methodology, health, problems or needs, and product development. This approach likely increased specificity, but it may also have excluded relevant publications that described early design work using different language, including terms such as digital health, technological innovation, co-design, participatory design, service design, or innovation processes occurring before a clearly defined product stage. For the same reason, the inclusion of product-related terminology may have reduced capture of studies addressing earlier innovation phases in which methodological exploration was already underway but not yet described as product development.

Third, the search was restricted to four databases, to publications in English, and to the period from 2016 onward. These choices were justified by the aim of focusing on recent technological health innovation literature, but they may have excluded relevant studies in other languages, databases, or publication types. In a field such as health innovation, this is particularly relevant because some practical design knowledge may appear in conference proceedings, institutional reports, or grey literature rather than in full journal articles.

Fourth, the review used qualitative thematic synthesis rather than meta-analysis. Given the heterogeneity of the included studies, this was the most appropriate strategy, but it also means that the conclusions are interpretive rather than statistically generalizable. Finally, several included papers described their methodologies unevenly across stages, especially in the earliest phases of discovery. As a result, some aspects of problem framing, prioritization, or interdisciplinary interpretation may have been conducted in practice but not fully documented in publication.

Despite these limitations, the review offers a useful synthesis of how design methodologies are being used in the early development of technological health innovations and highlights an important methodological gap: the limited availability of integrated approaches that connect problem discovery, evidence generation, contextual constraints, and explicit early-stage decision-making.

6. Conclusions

The studies included in this systematic review show that design methodologies are widely used in the development of technological health products to improve usability, strengthen contextual fit, and align solutions with the needs of patients, professionals, and other stakeholders. Human-centered, user-centered, and participatory approaches appeared repeatedly across the included literature and were especially relevant in contexts where success depended on acceptability, workflow compatibility, accessibility, and sustained engagement.

At the same time, the review reveals an important imbalance in how these methodologies are described and operationalized. Across the included studies, later phases such as prototyping, usability improvement, and refinement were usually reported more clearly than the earliest phases of problem framing, prioritization, and evidence-based narrowing of scope. The literature therefore provides useful methodological examples and strong general principles, but fewer integrated approaches that connect problem discovery, contextual analysis, implementation-related constraints, and explicit early-stage innovation decisions.

This has practical implications for scientific entrepreneurs, hospital innovators, and early-stage research teams. In these settings, the critical challenge is often not only how to build a good solution, but how to determine whether the underlying problem has been sufficiently understood to justify continued investment. The findings of this review suggest that future methodological work should focus on stronger discovery-to-decision frameworks that preserve the strengths of human-centered design while making early-stage reasoning, trade-offs, and viability assessment more explicit. Advancing that agenda may help reduce rework, improve real-world fit, and strengthen the translation of promising health innovations into viable products and services.

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Conflicts of Interest Statement

The author declares that there is no conflict of interests regarding the publication of this paper.

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Enhancing Dirty Data Detection via Large Language Models: Comparative Insights from ChatGPT, Gemini and Copilot

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ABSTRACT

Background: Dirty data, such as inconsistent categorical encodings, implausible values, duplicated records, and date/format errors, can compromise statistical inference and downstream decision-making. To support scalable data quality screening, LLMs are increasingly considered for data preparation tasks.

Methods: A tabular main dataset containing categorical and numerical variables was generated via stepwise prompting with ChatGPT and subsequently reviewed by domain experts. Seven representative data quality issues were injected (e.g., heterogeneous gender string variants, extreme BMI values due to decimal misplacement, gender–surgery incompatibilities, duplicates, admission date inconsistencies, character substitution [O↔0], and chronological/format errors). Using standardized prompts, the same datasets were uploaded to ChatGPT (v5.0), Gemini, and Copilot; queries were repeated across multiple attempts, and results were compared across models.

Results: Performance varied by error type. ChatGPT and Gemini struggled to consolidate semantically equivalent but differently written gender labels and produced incorrect frequency estimates, whereas Copilot identified more variants but still miscalculated proportions. All three models flagged extreme BMI outliers; Copilot, however, showed calculation errors in descriptive summaries. In detecting clinical plausibility constraints (e.g., gender–surgery mismatches) and structurally empty fields, models commonly misclassified empty cells as missing and, in some scenarios, generated hallucinated outputs. For duplicated records, ChatGPT and Gemini reliably detected duplicates but missed gender–surgery inconsistencies; Copilot's duplicate detection improved across attempts, and it more consistently captured gender-related mismatches. ChatGPT best identified admission date inconsistencies, while Gemini and Copilot failed to detect these errors. For character substitution, Gemini and Copilot detected the issue while ChatGPT did not. For chronological and date format errors, Copilot outperformed ChatGPT and Gemini.

Conclusions: LLMs can assist with rapid screening for certain data quality issues (notably outlier detection and some format-level anomalies), but they demonstrate inconsistent reliability for semantic normalization, rule-based clinical plausibility

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checks, and the interpretation of missingness. Human-in-the-loop verification and complementary deterministic validation rules remain essential when LLMs are used in data cleaning workflows.

KEYWORDS

Data quality, dirty data, data cleaning, large language models, ChatGPT, Gemini, Copilot, digital health

1. Introduction

High-quality clinical and administrative data are a prerequisite for reliable analytics and decision support; however, real-world datasets frequently contain missingness, inconsistencies, and format-level anomalies that are labor-intensive to detect and correct. Building on core data quality dimensions such as integrity, consistency, completeness, and accuracy, this study examines whether widely used large language models (LLMs) can serve as practical assistants for identifying common "dirty data" patterns in structured tabular datasets. Data integrity is defined as the completeness of the variables required for analysis and the conformity of the data to predefined formats. Data consistency refers to the absence of logically impossible values in the dataset and the coherence of data derived from related variables. Data integrity refers to the completeness of variables required for analysis and the conformity of data to predefined formats. Data consistency is defined as the absence of logically impossible values and the coherence of data derived from related variables. Data completeness and data accuracy involve identifying potential structural errors in the dataset through statistical analyses and ensuring the correctness of the data [1].

Dirty data are datasets that contain missing values, erroneous data entries, and inconsistencies [2]. Missing data, which are commonly encountered and negatively affect data quality, reduce statistical power and may lead to biased analyses [3]. Duplicate data increases frequency counts and introduces bias into analytical results. In medical datasets, duplicate records are frequently observed due to multiple patient encounters [4]. The presence of records in incompatible formats is common in clinical data and adversely affects data quality [5]. Unexpected outliers in variables may result from data entry errors, negatively impact data quality, and lead to misinterpretation of analytical results [6]. Recording data in different formats creates challenges during the analysis process; therefore, data are expected to conform to standardized formats during the data cleaning phase [7].

Data cleaning ensures that dirty data conform to data quality components and are suitable for statistical analyses. It improves the accuracy of analytical results, reduces bias, and enhances the reliability and reproducibility of findings [2]. The integration of data from multiple sources, along with the presence of missing values and inconsistent records, makes the data cleaning process particularly challenging [8]. Data cleaning is a time-consuming process that requires specialized expertise [9].

LLMs are actively involved in data analysis processes. Studies in the literature have examined their role as assistants in method selection and data analysis. Despite their advantages, they have limitations in performing advanced hypothesis testing. Expert oversight is therefore considered a requirement for statistical analyses conducted using LLMs [10]. They can save researchers considerable time in data cleaning and analysis tasks [11]. However, their capacity for data cleaning in text-based datasets remains limited [12]. In this study, we aim to evaluate the effectiveness of three different LLMs (ChatGPT, Gemini, and Copilot) in identifying errors within a dataset.

2. Methods

To comparatively evaluate the dirty data detection capabilities of three widely used LLMs, we designed a controlled, prompt-driven benchmarking workflow on a synthetic but clinically plausible tabular dataset. The main dataset was created iteratively with ChatGPT through a series of stepwise prompts designed in line with predefined variable types and coding schemes. Both the prompts and the generated outputs were reviewed by two independent domain experts. In addition, a third expert independently assessed the final dataset for overall correctness and identified potential data quality issues. All prompts were developed through consensus between two experts. For each scenario, the same modified dataset and a set of standardized prompts were used across ChatGPT 5.0, Gemini 2.5, and Copilot. Each model was run three times under identical conditions to assess consistency, sensitivity to different types of errors, and reproducibility during the study period (13–26 August 2026).

2.1 Main Dataset

The primary dataset, consisting of both categorical and continuous variables, was generated using ChatGPT through step-by-step prompts. The types of variables included in the dataset are presented in Table 1. The prompts and the generated data were reviewed by the experts involved in the study, and the accuracy of the results was independently evaluated by an external expert.

Categorical Variables	**Numerical Variables**
Gender (female, male)	Fasting Blood Glucose (mg/dL)
Surgical History (yes, no)	Age (year)
Surgery Type (cataract surgery, cholecystectomy, appendectomy, hernia repair, tonsillectomy, Cesarean section)	Height (cm)
	Body Weight (kg)
	Body Mass Index (kg/m^2)
	Pre-course quality of life scale score (1–10 points)
	Post-course quality of life scale score (1–10 points)
	Patient ID (6-digit ID number)

Table 1: Information for Variables

2.2 Prompts of LLMs and Data Quality Issues

For each application presented in Table 2, data quality issues consistent with the primary dataset were intentionally introduced. Using appropriate prompts, the dataset was uploaded to ChatGPT, Gemini, and Copilot, and each model was asked to identify the specified data quality issue. Within the primary dataset, inconsistencies between the variables gender and surgery type were present, including surgery diagnoses incompatible with patient sex. For each data quality query, the dataset was modified according to the data alterations specified in the table. The first data quality issue involved the presence of multiple data entries representing the category “female.” The second issue concerned the presence of outliers in the Body Mass Index variable due to data entry errors. The third issue consisted of surgery diagnoses incompatible with patient sex; specifically, Cesarean section procedures, which are not possible for male patients, were deliberately defined by the researcher. Duplicate records constituted the fourth data quality issue. The fifth issue involved the incorrect categorization of admission dates. In the sixth data quality issue, a character-level error was introduced by using the letter “O” instead of the numeral “0” (zero). The seventh data quality issue involved incorrect dates and inconsistencies in date formatting.

Data Quality Issues	**Prompts for LLMs**	**Data Quality Issues**
1	What is the number and percentage of females in this data set?	“Female”, “FEMALE”, “Kadın”, “KADIN”, “kadin” type inputs Gender-related data entry errors
2	Can you calculate descriptive statistics for “Body Mass Index” in this dataset?	Data entry error due to a misplaced decimal point Extreme values for BMI (269.27, 271.81) Gender-related data entry errors
3	Does this data set contain any incorrect or inappropriate data entries?	In two cases, a surgical diagnosis was recorded despite no surgery having been performed. Gender-related data entry errors (C/S for man, etc.)
4	Does this data set contain any incorrect or inappropriate data entries?	Duplicated data Gender-related data entry errors (C/S for man, etc.)

Data Quality Issues	Prompts for LLMs	Data Quality Issues
5	Does this data set contain any incorrect or inappropriate data entries?	Certain admission dates fall outside the past year; these records were still marked as "yes" (indicating admission within the last year). Gender-related data entry errors (C/S for man, etc.)
6	Does this data set contain any incorrect or inappropriate data entries?	Character substitution error (O ↔ 0) Gender-related data entry errors (C/S for man, etc.) Gender-related data entry errors (C/S for man, etc.)
7	Does this data set contain any incorrect or inappropriate data entries?	Chronological error (year 2034) Format error (day and month place exchange) Gender-related data entry errors (C/S for man, etc.)

Table 2: Data Quality Issues and Prompts for LLMs

2. Results

Table 3 presents the performance of the three LLMs in identifying different gender inputs. The models were tasked with detecting the frequency of the female category represented in the dataset using different lexical and formatting variations that convey the same meaning. It was observed that the ChatGPT and Gemini models failed to correctly identify formatting variations such as "Female," "FEMALE," or "Kadın," resulting in errors in frequency calculations. Copilot demonstrated comparatively better performance by recognizing multiple formatting variants; however, it still produced inaccuracies in frequency estimation.

Prompt	Dirty Data Problem	Expected Result	Number of Attempts	ChatGPT 5.0	Gemini	Copilot
What is the number and percentage of females in this data set?	"Female", "FEMALE", "Kadın", "KADIN", "kadin" type inputs Gender-related data entry errors (gender=male, surgery=Cesarean section)	50.20% female	1.	48.15% female	48.15% female	49.60% female
			2.	48.15% female	48.15% female	48.00% female
			3.	48.15% female	48.15% female	54.33% female
			Evaluation	**Failed to detect various forms of input** **Wrong calculation**		**Detection of various forms** **Wrong calculation**

Table 3: Performance of LLMs in Detecting and Quantifying Gender-Related Data Entry Variations

Table 4 presents the evaluation of extreme body mass index (BMI) values caused by misplaced decimal separators during data entry by the LLMs. ChatGPT and Gemini successfully identified the outliers across all three trials and accurately computed the descriptive statistics. In contrast, while Copilot issued warnings regarding the presence of outliers, it produced errors in the corresponding calculations.

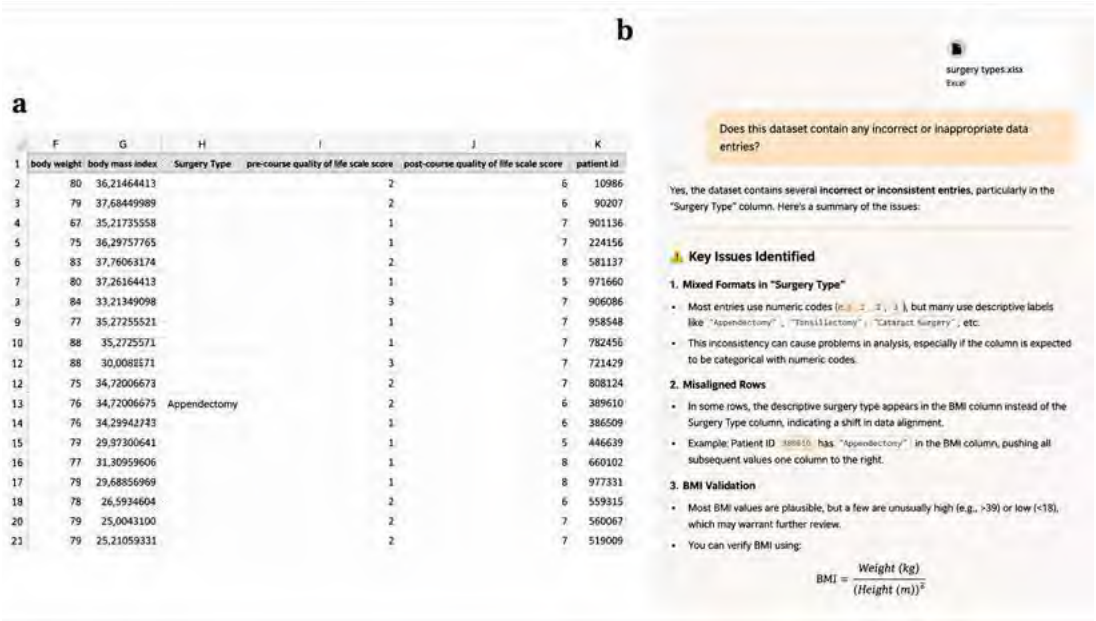
Prompt	Dirty Data Problem	Expected Result	Number of Attempts	ChatGPT 5.0	Gemini	Copilot
Can you calculate descriptive statistics for "Body Mass Index" in this dataset?	Data entry error due to a misplaced decimal point Extreme values for BMI (269.27, 271.81) Gender-related data entry errors (gender=male, surgery=Cesarean section)	Detection of extreme value	1.	Count: 243 Mean: 29.41 SD: 22.12 Variance: 489.35 Min: 21.80 25th percentile (Q1): 26.04 Median (Q2): 27.28 75th percentile (Q3): 28.98 Maximum: 271.81	Count: 243 Mean: 29.41 SD: 22.12 Minimum: 21.80 25th percentile (Q1): 26.04 Median (50th percentile):27.28 75th percentile (Q3): 28.98 Maximum:271.81	Count: 300 entries Mean: 27.38 Standard deviation: 11.26 Minimum: 21.80 Maximum: 271.81 Median: 26.67 25th percentile (Q1): 25.10 75th percentile (Q3): 28.69
			2.			
			3.			
			Evaluation	**Alert for extreme value**		**Alert for extreme value** **Wrong calculation**

Table 4: Performance of LLMs in Detecting and Analyzing Extreme BMI Values

Table 5 presents a comparison of model performance in detecting gender-related data entry errors and missing values. ChatGPT and Gemini failed to identify incorrect gender–surgery pairings and incorrectly classified cells that were intentionally left blank as missing data. Gemini reported no errors in the dataset during the first and last trials, whereas it incorrectly issued a missing data warning in the second trial. As illustrated in Figure 1, Copilot generated hallucinated outputs and misclassified cells that were intended to be empty as missing values. Although the dataset was correctly incorporated, the Copilot system incorrectly identified misaligned rows and referenced an ID that was not present in the data. This constitutes an instance of hallucination in LLMs.

Prompt	Dirty Data Problem	Expected Result	Number of Attempts	ChatGPT 5.0	Gemini	Copilot
Does this data set contain any incorrect or inappropriate data entries?	In two cases, a surgical diagnosis was recorded despite no surgery having been performed. (surgical history=no, surgery type=appendectomy) Gender-related data entry errors (gender=male, surgery=Cesarean section)	Inappropriate data entry detection of surgical type Detection of gender-related data entry errors	1.	Missing values: The Surgery Type column has 179 missing entries.	No noticeable anomalies	Both numeric codes and descriptive text entries in the "Surgical History" column Missing data Extreme BMI values
			2.		A few entries have a blank in "Surgery Type"	
			3.		No noticeable anomalies	
			Evaluation	**Erroneously flagged structurally empty fields as missing values** **Failed to detect gender-related data entry errors**	**Data error detection failed** **Erroneously flagged structurally empty fields as missing values** **Failed to detect gender-related data entry errors**	**Hallucination** **Erroneously flagged structurally empty fields as missing values** **Failed to detect gender-related data entry errors**

Table 5: Performance of LLMs in Detecting Inappropriate and Inconsistent Clinical Data Entries



	F	G	H	I	J	K
1	body weight	body mass index	Surgery Type	pre-course quality of life scale score	post-course quality of life scale score	patient id
2	80	36,21464413		2	6	10986
3	79	37,68449989		2	6	90207
4	67	35,21735558		1	7	901136
5	75	36,29757765		1	7	224156
6	83	37,76063174		2	8	581137
7	80	37,26164413		1	5	971660
8	84	33,21349098		3	7	906086
9	77	35,27255521		1	7	958548
10	88	35,2725571		1	7	782456
12	88	30,0088171		3	7	721429
12	75	34,72006673		2	7	808124
13	76	34,72006675	Appendectomy	2	6	389610
14	76	34,29942733		1	6	386509
15	79	29,97300641		1	5	446639
16	77	31,30959606		1	8	660102
17	79	29,68856969		1	8	977331
18	78	26,5934604		2	6	559315
20	79	25,0043100		2	7	560067
21	79	25,21059331		2	7	519009

Figure 1: Screenshot illustrating the dataset and an example of LLM hallucination output.

Table 6 presents the performance of the models in detecting duplicate records. Although ChatGPT and Gemini successfully identified repeated entries, they failed to detect gender-related inconsistencies in surgery types. Copilot did not identify duplicate records in the first trial but successfully detected them in subsequent trials. In contrast to the other models, Copilot consistently identified gender-related surgery type inconsistencies across all three trials. Across all three models, cells that were intentionally left blank were incorrectly interpreted as missing data.

<table>
<tr><th>Prompt</th><th>Dirty Data Problem</th><th>Expected Result</th><th>Number of Attempts</th><th>ChatGPT 5.0</th><th>Gemini</th><th>Copilot</th></tr>
<tr><td rowspan="4">Does this data set contain any incorrect or inappropriate data entries?</td><td rowspan="2">Gender-related data entry errors (gender=male, surgery=Cesarean section)

Duplicated data with two entries for each patient.</td><td rowspan="2">Detection of duplicated data

Detection of gender-related data entry errors</td><td>1.</td><td rowspan="2">A high number of duplicate entries

A large proportion of missing data in the Surgery Type variable entries</td><td rowspan="2">Duplicate rows

Missing values</td><td>Implausible or outlier values
Inconsistent surgery type entries
Missing or redundant data
Gender-specific mismatches</td></tr>
<tr><td>2.</td><td>Gender-specific surgery mismatches
Implausible age entries
BMI outliers
Missing or ambiguous surgery types
Duplicate or repetitive entries</td></tr>
<tr><td></td><td></td><td>3.</td><td></td><td></td><td>Gender-specific surgery mismatches
Implausible age entries
BMI outliers
Missing or ambiguous surgery types
Duplicate or repetitive entries</td></tr>
<tr><td></td><td></td><td>Evaluation</td><td colspan="2">Duplicated data detection

Failed to detect gender-related data entry errors

Erroneously flagged structurally empty fields as missing values</td><td>Duplicated data detection (attempt 2,3)

Detection of gender-related data entry errors

Erroneously flagged structurally empty fields as missing values

Failed to detect duplicated data (attempt 1)</td></tr>
</table>

Table 6: Performance of LLMs in Detecting Duplicate Records

Table 7 compares the models' abilities to detect data inconsistencies. Figure 2 presents representative screenshots of the date inconsistency detection process for ChatGPT and Gemini. Each model displays the data and reports its findings. The models were queried using a dataset in which the admission date fell outside the last year, yet the corresponding variable was incorrectly categorized as indicating an admission within the past year. ChatGPT successfully identified inconsistencies related to admission dates, whereas Gemini and Copilot failed to detect these errors. In addition, Gemini incorrectly classified cells that were intended to be empty as missing data, while Copilot emphasized that no errors were present in the relevant columns. Among the three models, ChatGPT demonstrated the best performance in detecting date-related errors. In this query, none of the three models was able to identify surgery diagnoses that were incompatible with patient gender.

Prompt	Dirty Data Problem	Expected Result	Number of Attempts	ChatGPT 5.0	Gemini	Copilot
Does this data set contain any incorrect or inappropriate data entries?	Certain admission dates fall outside the past year; these records were still marked as "yes" (indicating admission within the last year, for example). Reference date: 15 August 2025; admission date: 26 November 2023; admission within the past year: Yes (inconsistent). Gender-related data entry errors (gender=male, surgery=Cesarean section)	Data inconsistency detection	1. 2. 3.	Duplicate entries Missing data Admission date inconsistencies	Valid dates No duplicates Missing Values	Generally clean columns
			Evaluation	**Failed to detect gender-related data entry errors** **Detection data inconsistency**	**Erroneously flagged structurally empty fields as missing values** **Failed to detect gender-related data entry errors** **Failed to detect data inconsistency**	**Failed to detect gender-related data entry errors** **Failed to detect data inconsistency**

Table 7: Performance of LLMs in Detecting Date Inconsistencies

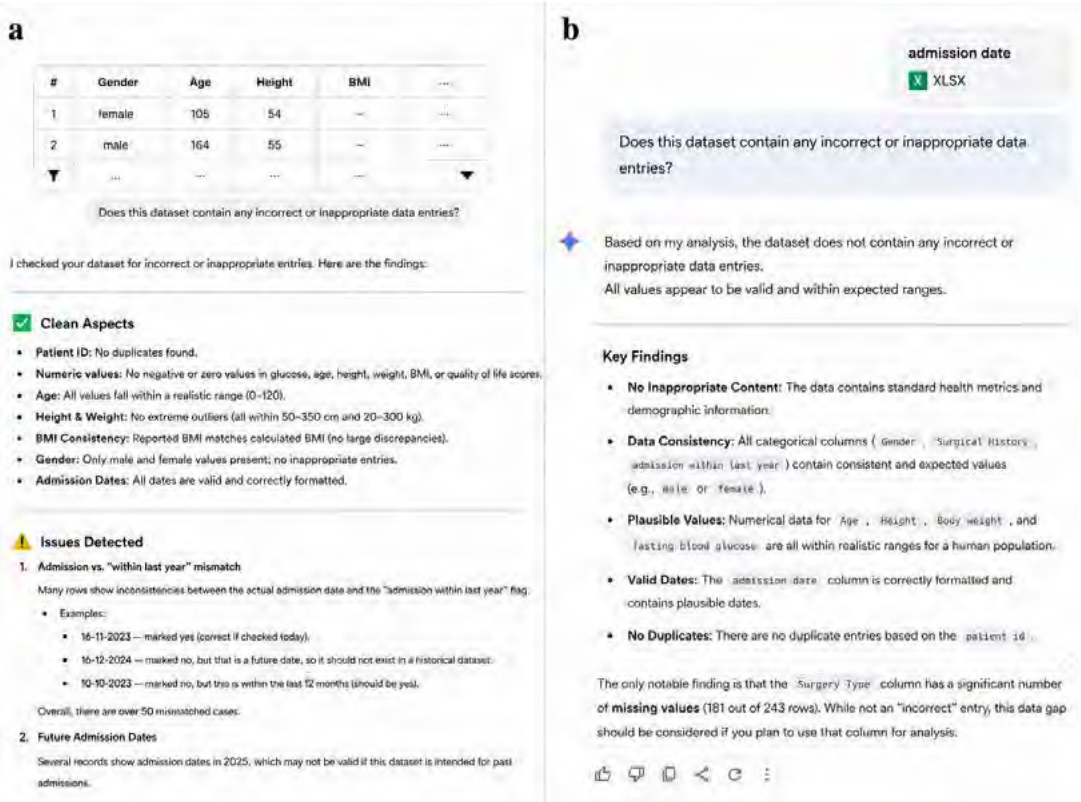


Figure 2: Screenshots for the data inconsistency detection of LLM (a. ChatGPT, b. Gemini).

Table 8 presents the performance of the LLMs in detecting character-level data entry errors. The dataset included instances in which the letter "O" was used in place of the numeral "0" (zero). While ChatGPT failed to detect this error, both Gemini and Copilot successfully identified it across all queries. ChatGPT incorrectly reported the presence of missing data and was unable to detect surgery diagnoses that were incompatible with patient gender. In addition to identifying character-level errors, Copilot demonstrated the strongest performance in detecting gender-incompatible surgery diagnoses.

Prompt	Dirty Data Problem	Expected Result	Number of Attempts	ChatGPT 5.0	Gemini	Copilot
Does this data set contain any incorrect or inappropriate data entries?	Character substitution error (O ↔ 0) Gender-related data entry errors (gender=male, surgery=Cesarean section)	Detection of character substitution error Detection of gender-related data entry errors (C/S for man, etc.)	1. 2. 3.	Missing values	Non-numeric character Incorrect data entries Incorrect data entries	Invalid patient IDs Biologically impossible surgical assignments Duplicate BMI values Outlier values
			Evaluation	**Failed to detect gender-related data entry errors** **Failed to detect character substitution error**	**Failed to detect gender-related data entry errors** **Detection of character substitution error**	**Detect gender-related data entry errors** **Detection of character substitution error**

Table 8: Performance of LLMs in Detecting Character-Level Data Entry Errors

Table 9 presents the models' performance in detecting date-related inconsistencies. The dataset included an impossible admission date (2034) and a date format mismatch, and the models were tasked with identifying these errors. ChatGPT and Gemini failed to detect either error across all three trials, whereas Copilot successfully identified both the invalid date and the date format inconsistency. In addition to failing to detect the errors, ChatGPT incorrectly issued missing data warnings. Although Copilot demonstrated the strongest performance in detecting this type of error, it also produced hallucinated outputs by generating results unrelated to the uploaded dataset.

Prompt	Dirty Data Problem	Expected Result	Number of Attempts	ChatGPT 5.0	Gemini	Copilot
Does this data set contain any incorrect or inappropriate data entries?	Chronological error (year 2034) Format error (day and month place exchange) Gender-related data entry errors (gender=male, surgery=Cesarean section)	Detect gender-related data entry errors Detect chronological error and format error	1. 2. 3.	Missing values No duplicates	Hallucination (different data set related findings)	Date format inconsistency Implausible admission data Gender-surgery Mismatches Outlier values
			Evaluation	**Failed to detect gender-related data entry errors** **Failed to detect chronological error and format error**	**Failed to detect gender-related data entry errors** **Failed to detect chronological error and format error**	**Detect gender-related data entry errors** **Detect chronological errors and format error**

Table 9: Performance of LLMs in Detecting Chronological and Date Format Errors

Discussion and Conclusion

Across seven common data-quality scenarios, encompassing both statistical and domain-specific logic errors, the three LLMs demonstrated complementary strengths alongside notable and consistent limitations. Overall, our findings suggest that LLM-based approaches can be useful for identifying more obvious anomalies, such as outliers and certain formatting inconsistencies. However, model performance was sensitive to how errors were represented (e.g., semantic versus syntactic forms) and was occasionally affected by miscalculations, misinterpretation of structurally empty fields, and sporadic hallucinations. These observations highlight the continued need for human oversight in clinical data-cleaning workflows.

LLMs may fail to evaluate semantically equivalent words within the same category due to differences in their orthographic representations [13]. In our study, ChatGPT and Gemini were unable to identify formatting variations such as "Female," "FEMALE," or "Kadın," whereas Copilot successfully detected these variants. This discrepancy can be attributed to differences in the models' sensitivity to surface-level formatting variations. LLMs are capable of detecting outliers in datasets [14]. Similarly, all three models in our study successfully identified outliers. Although Copilot detected the outliers, it made errors in the associated calculations. Although LLMs primarily operate by recognizing patterns within data, their capacity for medical reasoning remains limited [15]. In accordance with this limitation, none of the three models was able to detect inconsistencies between gender and surgery type during the initial queries. Previous studies have reported that LLMs can identify duplicate records during the data cleaning process [16], and all three models in our dataset demonstrated the same capability. LLMs are sensitive to missing data, and errors in missing data assessment have been previously reported [17]. Consistent with these findings, across different trials in our study, the models incorrectly classified cells that were intentionally left blank as missing data. For date-related inconsistencies, ChatGPT successfully detected errors associated with admission dates, whereas Gemini and Copilot failed to do so. Limitations in detecting data inconsistencies have been previously reported for LLMs [18], and our findings further support this evidence. Prior studies have demonstrated that LLMs exhibit limited performance in detecting character-level errors, such as character substitution, particularly in morphologically rich languages [19]. Our findings showed that Gemini and Copilot failed to detect character-level errors, whereas ChatGPT successfully identified such errors. This variation was attributed to differences in model sensitivity. Date-related errors and formatting inconsistencies are among the most commonly encountered issues in datasets [20]. Xu et al. [21] demonstrated that LLMs can effectively detect date, unit, numbering, and report template-related formatting errors in ophthalmic imaging reports. In our study, while ChatGPT and Gemini failed to identify date errors and formatting inconsistencies, Copilot successfully detected both. These findings suggest that the ability of these models to detect format- and date-related errors may depend on factors such as training data composition, contextual sensitivity, and error identification strategies.

In practice, LLMs should be positioned as assistive "first-pass" detectors rather than stand-alone validators, with results cross-checked through rule-based constraints (e.g., permissible category dictionaries, plausibility rules, and date-format validators) and expert review. While they offer rapid improvements in capability, they may still struggle with detection errors. Future studies should benchmark reproducibility across model versions and prompting strategies on real-world clinical datasets to clarify when LLMs add measurable value beyond conventional data quality tooling. These findings also point to several important directions for future research. First, the generation of benchmark datasets to assess the performance of different LLMs could help establish more standardized evaluation practices and provide a stronger foundation for their use in data cleaning processes. These datasets could be a standardized tool for researchers to test the capacity of new LLM tools in data cleaning tasks, and they serve as a tool to compare the capabilities of developing LLM tools. Second, attention should be given to the standardization of prompts used in LLM-assisted data cleaning, as well as to the validation of their effectiveness across different contexts. Standardized prompts can help produce more consistent outputs for every attempt at the same data cleaning task. Different data types are associated with distinct data quality issues. These data quality issues require appropriate handling methods. Interpreting standardized prompts on datasets with different structures and data types may help identify prompt workflows that are better suited to specific data-cleaning tasks. Researchers work with datasets of varying complexity, ranging from basic to highly structured forms. To use LLM tools effectively for data cleaning tasks, they require guidance and support. Educational resources that support researchers in designing specific prompts for a dataset may improve the effective and appropriate use of LLMs in practice. More advanced LLM tools may present accessibility challenges for researchers when attempting to integrate them into routine practice. The design of accessible and user-friendly LLMs capable of producing more consistent outputs across users would further strengthen their utility as assistive tools in data-cleaning workflows.

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Current Practices and Potential Technological Advancements in Multidisciplinary Tumor Board Workflows: A Scoping Review

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ABSTRACT

Introduction: Cancer remains a leading global cause of death, demanding coordinated, patient-centerd care. Multidisciplinary tumor boards (MTBs) improve outcomes but face time pressure and fragmented data. The German Virtual Reality Multidisciplinary Tumor Board (VR-MTB) project aims to address these gaps by developing an immersive platform that unifies clinical, imaging, and laboratory data and integrates AI-driven decision-support tools.

Methodology: A scoping review was conducted in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines for Scoping Reviews (PRISMA-ScR) to map existing research on tumor boards published between 2020 and 2025. Of 168 records identified, 57 met the inclusion criteria.

Results: The review identified current practices, workflows, and challenges in MTBs. While MTBs improve cancer care through collaborative decision-making, conventional settings face inefficiencies due to fragmented data, time constraints, limited participants engagement, and poor system interoperability. Virtual MTBs (vMTBs) gained traction during the COVID-19 pandemic, showing potential for greater efficiency and inclusion. Barriers to adopting tools like extended reality (XR) and artificial intelligence (AI) include integration issues, resource constraints, resistance to change, and usability concerns, despite demonstrated value in pilot implementations.

Discussion and Conclusion: This scoping review mapped current MTB practices, revealing key workflow gaps and barriers to adopting advanced tools like XR and AI. While vMTBs show promise, successful digital transformation requires standardized processes, stakeholder engagement, integration with hospital systems, and further real-world evidence to ensure clinical impact and user adoption.

KEYWORDS

Multidisciplinary tumor boards (MTBs), cancer care, healthcare workflows, extended reality (XR), artificial intelligence (AI)

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1. Introduction

1.1 Cancer

Cancer remains a major global health issue and a leading cause of death [1, 2]. As per GLOBOCAN 2022 data from the International Agency for Research on Cancer (IARC), approximately 20 million new cancer cases and 9.7 million deaths were recorded worldwide. Lung cancer accounted for nearly 2.5 million cases, making it the most commonly diagnosed, followed by breast, colorectal, prostate, and gastric cancers [3].

Early detection significantly improves survival and plays a critical role in enhancing prognosis and outcomes [4].

1.2 Tumor Boards

Effective cancer treatment requires collaboration among specialists from various fields. By sharing expertise and tailoring care plans to patient needs, professionals ensure personalized and current treatment. There is a growing preference for multidisciplinary team (MDT) strategies in cancer care [5]. The MDT concept emerged in the United Kingdom (UK) during the 1990s and gained traction following the 1995 Calman-Hine plan, which sought to standardize high-quality cancer care across regions [6].

Multidisciplinary management (MDM) in oncology optimizes care by integrating expertise across the entire cancer care continuum [7]. It enhances diagnostic accuracy, treatment planning, and protocol adherence [8]. Multidisciplinary tumor boards (MTBs), also known as multidisciplinary team meetings (MDTMs), are forums where specialists jointly plan individualized cancer treatment [9]. Terms like tumor boards (TBs), tumor conferences, or multidisciplinary cancer conferences (MCCs) are used interchangeably in some institutions [10].

1.3 VR-MTB project

The VR-MTB (Virtual Reality Multidisciplinary Tumor Board) initiative, supported by the German Federal Ministry of Research, Technology, and Space (BMFTR), seeks to enhance cancer care through more effective MTBs. While interdisciplinary oncology teams support optimal treatment decisions, obstacles such as time constraints, fragmented data, and limited imaging access hinder collaboration [11, 12].

To address these issues, the project is developing a virtual reality (VR) platform that merges clinical, imaging, and lab data in a shared immersive environment. Oncology teams can interact with three-dimensional (3D) images and patient data collaboratively in real time. The platform is designed via a needs assessment and integrates artificial intelligence (AI)-driven tools for transcription and organization, improving documentation and interoperability with hospital systems. Ultimately, VR-MTB aims to enhance workflow and clinical decision-making. The solution is being designed for scalability and global adoption.

1.4 Research Questions

This literature review, part of Work Package 2 (WP-2) of the VR-MTB project, focuses on identifying research trends and gaps. Research questions (RQs) were framed using the SPICE framework (Setting, Perspective, Intervention, Comparison, Evaluation), commonly used to evaluate healthcare service delivery and technology implementation [13].

Initial RQs were refined with support from ChatGPT [14], and target clinical, technical, and ethical-regulatory domains. Due to the volume of findings, this review addresses the following five RQs:

1. What are current workflows, practices, and standard operating procedures (SOPs) within multidisciplinary tumor boards?
2. What challenges and inefficiencies are experienced by healthcare professionals during tumor board sessions?
3. How can virtual/remote participation affect team dynamics and collaboration quality?
4. What are the main organizational barriers to adopting advanced tools such as extended reality (XR) and AI-driven decision support technologies in multidisciplinary oncology teams?
5. What strategies are most effective for engaging and convincing clinical, administrative, and information technology (IT) participants to actively involve in the implementation and evaluation of a VR-enhanced multidisciplinary tumor board (VR-MTB) platform?

2. Methodology

This scoping review followed the PRISMA guidelines for Scoping Reviews (PRISMA-ScR) [15, 16]. Scoping reviews are systematic, iterative methods for synthesizing knowledge that map the scope, variety, and characteristics of the literature while identifying research gaps [17]. Article selection followed the PRISMA flow chart, using a three-phase diagram to ensure consistency in data collection [18, 19].

The results of the literature review are shown in Figure 1.

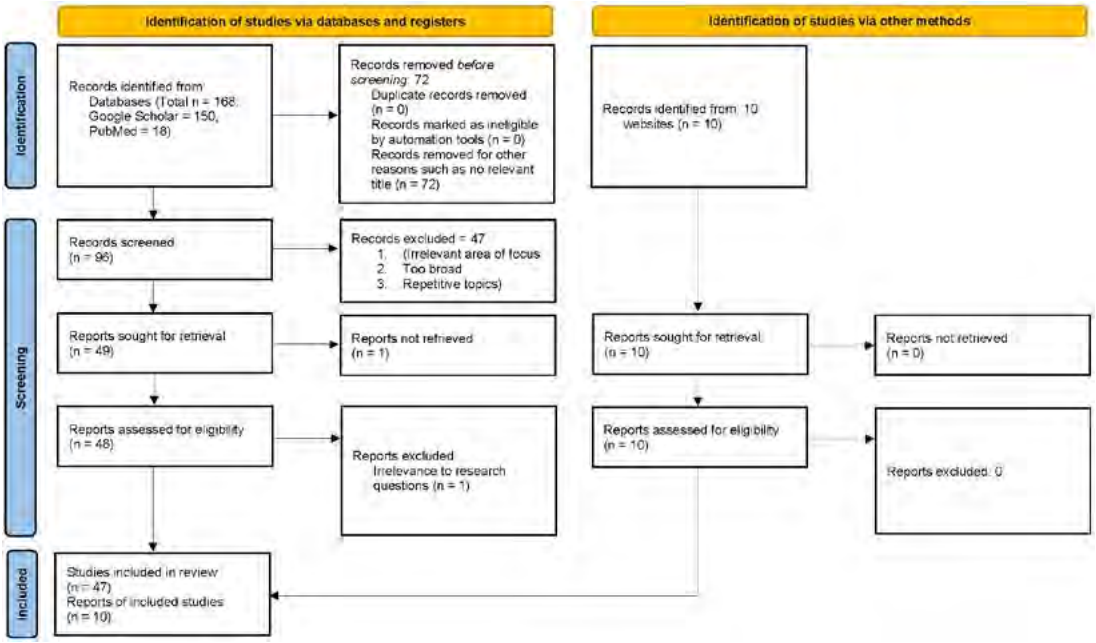


Figure 1: PRISMA flow diagram.

2.1 Identification

A comprehensive search was conducted in Google Scholar and PubMed between March and April 2025, using English terms without restricting study types. Most publications dated from 2020 to April 2025. The SciSpace AI platform was employed to refine the review and align it with research questions [20].

- Searches were research question-driven using semantic matching
- Full-text analysis was performed via its chat interface for deeper insight

Search Terms

Boolean operators (AND/OR) and quotation marks refined the search strategy. The following terms were used:

- ("tumor board" OR "tumor conference" OR MTB OR MDT) AND (workflow OR clinical OR healthcare OR oncology)
- ("tumor board" OR "tumor conference" OR MTB OR MDT) AND (drawback OR disadvantage OR challenge OR cons OR problem OR limitation OR barrier OR obstacle OR "clinical difficulty")
- ("clinical outcome" OR efficacy OR effectiveness OR adherence OR patient care OR survival OR "patient experience") AND ("tumor board" OR "tumor conference" OR MTB OR MDT)
- (user needs OR clinical requirements OR "essential functionalities") AND ("tumor board" OR "tumor conference" OR MTB OR MDT)
- (adoption OR integration OR implementation OR acceptance) AND (“virtual reality” OR “augmented reality” OR “mixed reality” OR “extended reality”) AND ("tumor board" OR "tumor conference" OR MTB OR MDT OR (AI OR "artificial intelligence"))

Out of 168 articles identified (Google Scholar = 150, PubMed = 18), 72 were excluded based on title.

2.2 Screening

Titles and abstracts were initially screened for relevance. Of 96 records, 47 were excluded due to irrelevance, broad scope, or duplication. Inclusion criteria matched the research questions, while exclusions applied to non-English texts, pre-2020 publications, and duplicates. Two pre-2020 studies were retained due to relevance. Full texts were sought for 49 articles, with 48 successfully retrieved. Bibliography citation screening added 10 records (websites = 10).

2.3 Inclusion

A total of 57 records were included (47 from databases, 10 from other sources). Mendeley was used for reference management [21]. All sources were cited in accordance with the journal-specific Vancouver style [22]. The SciSpace Paraphraser tool (by PubGenius Inc.) was used in "Fluent" mode to improve readability [20].

3. Results

3.1 Conventional MTBs

3.1.1 Current workflows and tools used in MTBs

Regular Meetings: Tumor board meeting frequency varies by institution, specialty, patient volume, and cancer type. The American College of Surgeons' Commission on Cancer (CoC) mandates multidisciplinary cancer conferences, with each program defining and documenting their meeting schedule in official policy [23]. CoC Cancer Program standards specify that tumor boards should meet weekly or monthly, depending on the institution’s accreditation. Surveys show 58 % of physicians attend weekly and 25 % monthly [24, 25]. Centers with 25 or more new cancer cases per month usually hold weekly meetings, while those with fewer than 15 cases often meet biweekly or monthly [26, 27]. Regular meetings ensure multidisciplinary evaluation so all treatment options like surgery, radiotherapy, or endoscopic resection are thoroughly considered.

Interdisciplinary Decision-Making: Discussions involve specialists from surgery, oncology, radiology, pathology, and supportive care to address all clinical aspects. Allied health professionals including nurses, psycho-oncology experts, and nutritionists also contribute, with palliative care experts involved when needed [24, 25]. Junior faculty, fellows, and residents participate, contributing to education and career development [28].

One study found 66 % of 102 patients were willing to engage in tumor board discussions, with clearer recommendations linked to greater treatment confidence [27].

Before the Meeting

Procedures vary across institutions due to differing resources and systems. The National Cancer Control Programme (NCCP) emphasizes standardized documentation through tumor-specific SOPs for registration, preparation, execution, and reporting. These are updated by the NCCP Tumour Leads Group, with general guidance for hospitals lacking dedicated teams [29].

Patient Selection and Eligibility Screening: The workflow prioritizes complex or unclear cases, typically managed by cancer care coordinators or junior doctors [30].

Preparation begins with selecting eligible patients—those who:

- Have relapsed or suffer from treatment-resistant malignancies
- Have exhausted conventional therapies
- Show limited tolerance for standard treatments
- Have rare tumors lacking guideline-directed options

Selection is initiated by any provider, with criteria varying by institution. Once deemed eligible, patients are registered for review by the treating physician or directly [31]. Patients are usually informed beforehand that their case will be discussed [27].

Case Submission: Before each meeting, doctors use standardized forms to submit administrative details, history, exam findings, imaging (magnetic resonance imaging [MRI], computed tomography (CT), positron emission tomography (PET)), labs, pathology, and genomic data [25]. Workflows often involve manual data extraction from unstructured sources like pathology reports and referral letters [32]. Once identified, registrars or specialists input key information into standardized electronic systems—a time-consuming process requiring clinical expertise [32].

A study reported Microsoft Access was used to create an MDT template for real-time entry, allowing staff to input and access full patient data, while a senior clinician compiled key points [33]. Some hospitals use Onkostar, which offers structured templates for diagnosis, surgery, pathology, and tumor board input [32]. These ensure consistency and support full case assessment [32]. An agenda with patient demographics, diagnoses, and initial treatment details is shared before meetings [34].

During the Meeting

Meeting Place: Meetings occur in designated rooms. Breast and skin boards use larger structured rooms, while blood and marrow sessions take place in smaller, informal settings to foster deeper discussion [25, 34].

Meeting Protocol and Data Management: Effective MTBs rely on strong leadership. A leader guides discussion and maintains focus. Some centers rotate chairs or use non-voting leaders to encourage openness and reduce bias [30]. Sessions include detailed review of imaging, pathology, and treatment plans like surgery or radiotherapy. Structured agendas ensure discussions stay within time limits, overseen by the chair [29].

Number of Cases: TBs typically review 15–50 cases weekly, varying by institution and cancer type [34].
Meeting Duration: Most sessions last 1–2 hours, with 3–4 minutes per case. One study noted 657–741 cases monthly at one center, averaging 20 per meeting [25, 34].

Tools: Rooms have projectors and large screens for rosters, pathology, imaging, and clinical summaries [34]. Without integrated systems, some boards still use PowerPoint for slides and imaging [34]. A standardized template is used to document discussions, ensuring complete clinical records [29].
Digital tools, including web apps, have been tested for real-time documentation [35].

Final Decision: Recommendations result from consensus discussions. Each specialist contributes their perspective, often leading to revised diagnoses, adjusted treatments, or further tests for personalized care [28, 29].

After the Meeting

Documentation and Protocols: Decisions are documented in patient records to ensure traceability and compliance. The primary consultant implements plans and communicates with patients and general practitioners. All decisions are included in protocols reviewed annually to incorporate new evidence and feedback [25, 29, 36].

Adherence to Guidelines: Recommendations are reviewed for compliance with evidence-based standards [36, 37].

Patient Inclusion and Satisfaction: Recommendations are shared with patients and physicians. Patient preferences are considered, and workflows promote clinical trial participation. A 93 % adherence rate indicates strong communication and follow-through [36].

3.1.2 Challenges

Preparation for Meetings: Traditional MTB preparation lacks standardization, with inconsistent organization and undefined resource needs. This variability causes inefficiencies, insufficient readiness, and missing critical data [38]. A recent survey found many healthcare professionals struggle to attend TBs due to scheduling conflicts. Only 43.9 % of radiologists reviewed imaging beforehand, potentially reducing decision quality [39]. Patient information is often sent via e-mail to an administrative assistant who compiles cases. This fragmented process uses multiple tools—e-mail, Word, PowerPoint—requiring manual data extraction and reformatting [40].

Protocols depend on data from radiology, pathology, and clinical assessments, often stored in separate systems. Integration usually requires manual transfer from hospital information system (HIS) to platforms like Onkostar, causing delays and errors [32]. SOPs rely on manual entry and review, following internal standards emphasizing accuracy but are prone to unintentional errors due to the manual nature [40]. Traditional workflows involve disconnected stages and communication channels, resulting in delays and disrupted meeting productivity [40].

Complexity of Cases: Managing advanced, recurrent, or metastatic cancer is complex due to patient variability and comorbidities, complicating consensus [24]. Case selection and preparation are often inefficient. Clearer criteria could ensure that relevant and complex cases receive focus [41]. Not all cases get equal attention. Complex ones may be reviewed thoroughly, while early-stage or elderly patients' cases may be overlooked, affecting care. Filtering by coordinators or junior staff may introduce inconsistency or bias [26].

Time-Consuming Processes: Preparation time varies by cancer type, specialty, and institution. MTBs are resource-intensive, limiting scalability. Preparing a single case may take 15 to 90 minutes across systems like PubMed and organizational systems [42]. One study reported 11 hours spent preparing 159 cases—over 4 minutes per case—delaying workflow and adding stress during urgent decision-making [40]. TB case discussions average 5.5 to 6.5 minutes, indicating a need for better data consolidation tools [36, 38]. Face-to-face meetings require significant time, with clinicians spending 1.25 million man-hours annually and 50 extra hours monthly on case evaluations [39]. Ineffective time management is common; skilled moderators and improved strategies are needed [41].

TBs often review many cases quickly—for example, 30–50 in under two hours—leading to rushed discussions [34]. Blood and marrow meetings may allow longer discussions but can last up to four hours, risking inefficiencies and participant fatigue [34].

Increased Potential for Errors: Fragmented data forces clinicians to manually search EHRs, increasing risks of errors like incorrect medical record numbers (MRN) or missed cases [40].

Limited Multidisciplinary Engagement: Discussions are often one-way, with physicians presenting and limited input from nurses or dieticians, reducing collaboration [34]. Rigid formats in breast and cutaneous boards create passive audiences, limiting feedback and hindering adaptive treatment planning [34]. Room layouts, especially in some sessions, reinforce hierarchy by placing surgical oncologists at the front, discouraging open discussion [34].

Resource Limitations: Limited specialist access in some areas reduces MTB effectiveness. Mini tumor boards may be used but face similar inefficiencies [24, 41].

Lack of Interoperability: Many health information technology (HIT) systems lack interoperability, delaying information access during meetings and hindering decisions [38]. Switching between tools like e-mail, Word, and PowerPoint reduces efficiency. Asynchronous e-mails delay preparation, limiting review time [40].

Professionals stress the need for tools that integrate clinical, radiological, and molecular data while connecting to current knowledge and collaboration features [43]. Desired features include fast presentation creation, treatment documentation, multi-user access, 3D Digital Imaging and Communications in Medicine (DICOM) support, and an intuitive, easy-to-learn interface [44].

Usability Issues: Most TB tools focus on narrow tasks and lack comprehensive capabilities, frustrating users. Advanced tools like XR and AI systems often have poor usability, reducing adoption [38].

3.1.3 Role of MTBs in Cancer Treatment and Decision-Making

Patient-Centered Care: MTBs prioritize patient needs, values, and preferences, supporting informed decisions. This approach is part of Germany's national cancer plan and clinical guidelines [24, 36].

Improving Outcomes: MTBs improve cancer assessment, organ preservation, and quality of life. Greater involvement correlates with better outcomes [24, 39]. One study showed patients attending three or more MTBs had significantly better survival, suggesting regular discussions support improved outcomes [45].

Although MTBs are common in cancer care, their effectiveness and impact on patient outcomes vary and are not consistently evaluated across healthcare settings [28].

Educational Platform: MTBs support knowledge exchange and continuous learning to keep clinicians updated [24].

Tumor Board Simulation: Simulated MTBs improve preparedness in early medical education [46–48].

3.2 Virtual MTBs

3.2.1 Adoption and Use

The Coronavirus Disease 2019 (COVID-19) pandemic accelerated adoption of virtual MTBs using platforms like ZOOM, enabling remote collaboration and timely decision-making. Virtual multidisciplinary tumor boards (vMTBs) allow all relevant specialists to participate regardless of location [24, 36].

3.2.2 Benefits and Opportunities

A study found that the number of cases reviewed in MTBs is key to effectiveness, with similar case volumes and discussion quality in both in-person and virtual formats [39]. Surveys show many MTB participants find virtual formats more time-efficient and convenient, with strong support for continued use of virtual or hybrid meetings, reflecting a shift toward flexible arrangements [39]. Virtual TBs can improve patient experience by enabling quicker specialist collaboration and decision-making, leading to faster treatment starts and potentially better outcomes through holistic care [39].

3.2.3 Challenges

Although teleconferencing platforms like Zoom became popular during COVID-19, some referring physicians were reluctant to adopt them, citing challenges in integrating teleconferencing into their routines, which could hinder collaboration [36].

3.3 Novel Digital Solutions in MTBs

This section focuses on the key barriers and enabling factors influencing the adoption and implementation of advanced digital solutions, including XR (VR/AR/MR) and AI, in MTBs.

3.3.1 Challenges

Integration with Existing Systems

Clinical workflows span electronic medical records (EMR), labs, and imaging. XR and AI must integrate seamlessly. Research on Navify Tumor Board highlights poor integration with hospital systems as a key barrier [49].

Resistance to Change

Clinicians often resist new technologies due to unfamiliarity or distrust [38]. Concerns include reliability and potential disruptions to established workflows [50]. Staff using e-mail and manual processes are often reluctant to transition due to entrenched habits [40]. Advanced technologies require workflow changes, and ingrained routines cause resistance [50].

Resource Constraints

Financial limitations hinder investment in XR and AI. Costs of acquisition, deployment, and training are often prohibitive [38]. Licensing, hardware, and integration expenses significantly impact adoption [49].

Data Privacy and Security Concerns

Handling sensitive data raises concerns over privacy, requiring compliance and strong safeguards [38].

Lack of Evidence on Effectiveness

Literature lacks consensus on XR and AI's clinical impact. This uncertainty makes stakeholders hesitant [38]. Clear evidence is needed to show benefits to outcomes and workflow. Without it, skepticism remains [50]. If clinicians view tools as barriers, adoption will stall. The NAVIFY study highlights the value of standardized processes and stakeholder involvement [49].

Cybersickness

Cybersickness causes nausea, dizziness, and headaches during XR use. It's visually induced without motion and varies by user experience [51, 52]. Causes include display resolution and wide fields of view. Poor calibration worsens symptoms, even with improved motion tracking [53, 54].

3.3.2 Adoption and Implementation Strategies

Early Engagement

In the NAVIFY project in Taiwan, clinical, admin, and IT stakeholders were engaged early, improving ownership and reducing resistance [49]. Healthcare providers shared experiences in feedback sessions, helping developers tailor features to real-world use. Clinicians tested the system during routine care, helping resolve issues early [50].

Clear Communication of Benefits

Clear communication of benefits, such as time savings and improved information management, can support the adoption of digital MTB solutions [49]. Evidence from pilot studies can also be used to demonstrate how reductions in preparation and discussion time may improve patient care and streamline clinical workflows [49].

User-Focused Design and Co-Creation

NAVIFY was co-developed with clinician input, improving usability and alignment with practice. Ongoing feedback shaped improvements, strengthening trust and functionality [50]. In the NeuroVis project, users shaped design for radiosurgery planning [55]. In the MR-HNTB study, users tested prototypes in simulations, identifying strengths and usability barriers [56]. In IMHOTEP, participants gave usability and clinical feedback via standardized questionnaires [57]. NAVIFY's flexible development allowed continuous updates and collaboration [50].

Education and Staff Training

A tumor board nurse navigator coordinated NAVIFY rollout, offering training and support [50]. Tailored programs should address each group's priorities—workflow for clinicians, integration for IT. Ongoing support ensures engagement and addresses issues quickly. Practical training builds confidence and encourages adoption [49]. Without training, clinicians may struggle to adopt new tools [38]. Studies highlight the value of live training, video tutorials, and standard operating procedures to help users adapt to digital tools [40]. For NAVIFY Tumor Board, a tumor board nurse navigator was added to coordinate training and team organization, ensuring a smooth and efficient transition to the digital tool [50].

NAVIFY Tumor Board was initially introduced with a manual upload option to ease healthcare professionals' transition. The phased rollout, combined with ongoing training and support, allowed clinicians to adapt gradually and ensured consistent learning and problem-solving across teams [50].

Demonstration of Real-World Benefits

NeuroVis developers showcased six cases to demonstrate clarity and efficiency using features like clipping planes and adjustable opacity [55]. Scalability across HoloLens versions and integration with machine learning boosted confidence in future potential [55].

4. Discussion & Conclusion

4.1 Research Aim and Methodological Foundation

The aim of this scoping review was to identify gaps in the current literature for TB workflows that might guide a future systematic review. A PRISMA-ScR–guided search, conducted across Google Scholar and PubMed yielded 168 records; following the removal of duplicates and a three-phase screening process. 47 articles were ultimately included in our study.

4.2 Limitations & Strengths of the Study

4.2.1 Limitations

This review used the PRISMA-ScR methodology with PubMed, Google Scholar, grey literature, and citation tracking but did not cover all databases. The 2020–Q1 2025 date range excluded earlier foundational studies, and English-only screening likely biased results toward North American and Western European sources.

4.2.2 Strengths

The strengths include methodological rigor and transparency; the protocol was adhered to PRISMA-ScR checklists, and utilized concrete framework for research questions. Reviewers conducted screening and data extraction, enhancing inter-rater reliability.

4.3 Interpretation of Findings

4.3.1 Current MTB Landscape and Workflow Gaps

RQ-1: What are current workflows, practices, and standard operating procedures (SOPs) within multidisciplinary tumor boards?

MTBs are an essential part of oncology care, enabling collaborative, case-based discussions to guide evidence-based treatment decisions. Current clinical workflows typically involve regularly scheduled meetings, either weekly or monthly, where multidisciplinary teams of specialists assess patient cases using standardized templates and shared clinical data [25, 34]. SOPs guide many aspects of these workflows, including patient selection, case documentation, meeting structure, and post-meeting follow-up [29]. However, SOP implementation varies between institutions depending on resources, cancer type, and national directives.

Several workflow gaps remain. Data collection is still largely manual, requiring extraction from unstructured clinical documents such as pathology reports and referral letters, which can be time-consuming and error-prone [32]. Some institutions use digital tools like Microsoft Access templates or platforms such as Onkostar to support structured documentation, yet adoption is inconsistent [32, 33]. Additionally, tools like PowerPoint are still used in settings lacking integrated systems, limiting data accessibility and real-time decision-making support [34]. While most MTBs follow a structured process, there is limited standardization across institutions in how patient preferences are integrated into decision-making, and how feedback is used to improve MTB quality [27, 36].

In conclusion, although MTBs are built on coordinated and partially standardized practices, significant variability exists in SOPs, documentation workflows, and digital tool usage. Future improvements should focus on increasing workflow automation, standardizing digital platforms, and enhancing patient-centered practices to strengthen the impact of MTBs on cancer care delivery.

RQ-2: What challenges and inefficiencies are experienced by healthcare professionals during tumor board sessions?

Despite their essential role in multidisciplinary cancer care, MTBs face several persistent challenges that hinder clinical efficiency. One of the primary issues is the inconsistent and time-consuming preparation for meetings. The lack of standardized SOPs across institutions leads to variability in how cases are selected and organized, often resulting in incomplete case information and inefficient use of meeting time [40, 50]. Manual data collection, fragmented workflows using non-integrated tools like e-mail, Word, and PowerPoint, and the need to gather information from isolated systems such as HIS and imaging archives further exacerbate delays and increase the potential for documentation errors [32 ,40].

Time management is a widespread concern. Preparing a single case can require up to 90 minutes, while TB meetings often handle 30 to 50 cases within a tight timeframe, leading to rushed discussions and participant fatigue [34, 42]. Moreover, conflicting schedules and heavy workloads limit the participation of key professionals such as radiologists, which may compromise the quality of case reviews [39].

Multidisciplinary engagement also remains limited. Presentation formats are often rigid, and hierarchical seating arrangements discourage open discussion. Contributions from allied health professionals are minimal unless explicitly invited, which undermines the collaborative nature of MTBs [34]. Additionally, complex or advanced cases dominate the agenda, while early-stage or elderly patients may receive insufficient attention, reflecting inconsistencies in case prioritization [24, 26].

Resource limitations and lack of interoperability between HIT systems further challenge TB operations, especially in under-resourced or rural settings. The absence of integrated platforms delays access to relevant data and necessitates repetitive tasks that reduce [43, 50]. Even where digital tools are adopted, usability issues, steep learning curves, and insufficient multi-user functionalities hinder widespread clinical adoption [44].

In summary, conventional TB settings are constrained by fragmented processes, poor interoperability, limited multidisciplinary input, and usability limitations in existing digital tools. Addressing these challenges through streamlined data integration, well-defined SOPs, improved time and resource management, and user-centered digital platforms is crucial for enhancing the efficiency and clinical value of MTBs.

RQ-3: How can virtual/remote participation affect team dynamics and collaboration quality?

vMTBs have improved accessibility and flexibility, allowing wider participation from specialists regardless of location. Studies show that discussion quality and case volume remain consistent with in-person meetings [39]. Many professionals report time savings and greater convenience, supporting the continued use of virtual or hybrid formats [39].

However, some clinicians find it difficult to integrate teleconferencing into their routines, which may affect collaboration depth [36]. While vMTBs enhance operational efficiency and access to expertise, maintaining engagement and addressing usability concerns are essential for sustaining collaborative quality.

4.3.3 Implementation Barriers

RQ-4: What are the main organizational barriers to adopting advanced tools such as XR and AI-driven decision support technologies in multidisciplinary oncology teams?

The adoption of advanced visualization and AI-driven decision support tools in oncology teams faces multiple clinical and organizational barriers. A major obstacle is the limited integration of these technologies with existing hospital systems such as EMRs and imaging platforms, which creates

workflow inefficiencies and delays [49]. Resistance to change is also common, as many healthcare professionals are hesitant to move away from familiar tools like e-mail and PowerPoint toward digital systems they may perceive as complex or untested [40, 50].

Significant financial constraints further limit adoption. The cost of software licensing, XR hardware, training, and ongoing maintenance can be prohibitive, especially in resource-constrained settings [49]. Concerns around data privacy and regulatory compliance also discourage institutions from deploying new digital systems that manage sensitive patient data [50].

Clinicians and administrators remain cautious due to a lack of strong clinical evidence supporting the effectiveness of XR and AI in improving outcomes or efficiency. The emerging nature of these technologies, combined with limited real-world validation, adds to the skepticism [38]. Additionally, user discomfort such as cybersickness—triggered by head-mounted display (HMD) settings—can negatively affect the experience and limit widespread use [51, 54].

In summary, successful adoption of XR and AI in MTBs requires addressing integration challenges, reducing costs, improving usability, and generating robust clinical evidence to earn trust among healthcare professionals and participants.

RQ-5: What strategies are most effective for engaging and convincing clinical, administrative, and IT participants to actively involve in the implementation and evaluation of a VR-enhanced multidisciplinary tumor board (VR-MTB) platform?

Successful adoption of a VR-MTB platform requires early and active engagement of clinical, administrative, and IT participants. Involving healthcare providers (HCP) from the initial design phase fosters ownership and minimizes resistance, as seen in projects like NAVIFY and NeuroVis where users co-developed features based on real clinical workflows [38, 55]. Co-creation ensures the tool aligns with actual user needs and promotes long-term trust in the system.

Clear communication of benefits is also essential. Demonstrating how VR tools reduce manual data handling and improve decision-making efficiency helps participants recognize their practical value [49]. Training programs tailored to different roles, supported by live sessions, tutorials, and continuous support, further reduce hesitation and promote confidence in using new technologies [40, 50].

Dedicated roles, such as a tumor board nurse navigator, can streamline implementation by coordinating training and providing hands-on support during the rollout [50]. Finally, showcasing real-world use cases and clinical scenarios reinforces the platform's relevance and scalability, helping participants visualize long-term benefits and encouraging sustained participation [55].

In summary, a combination of early involvement, user-centered design, clear communication, customized training, and real-world validation is key to gaining stakeholder buy-in for VR-enhanced MTB platforms.

4.4 Recommendations

4.4.1 Recommendations for Future Research

Future research should concentrate on a number of crucial areas in order to enable the integration of developing technologies and fix the shortcomings found in the present MTB operations.

First, in clinical cancer settings, solid real-world assessments of XR and AI-based solutions are required. While preliminary studies and pilot implementations suggest improvements in efficiency and collaboration, further longitudinal and multi-center studies are required to assess their impact on clinical outcomes, decision quality, and patient experience.

Second, future investigations should explore the cost-effectiveness and scalability of these technologies. Comprehensive economic evaluations, including implementation costs, maintenance requirements, and return on investment, are essential to support informed decision-making by healthcare institutions.

Third, standardization and interoperability should be the main topics of study. It is essential to conduct research on how XR and AI platforms may be integrated with current hospital systems, including laboratory databases, imaging systems, and electronic health records (EHRs). To facilitate smooth data interchange and lessen workflow fragmentation, more research should be done on the usage of standardized frameworks like Digital Imaging and Communications in Medicine (DICOM) and Fast Healthcare Interoperability Resources (FHIR).

Lastly, future studies should focus on ethical, legal, and social implications (ELSI), such as user trust, data privacy, and the transparency of AI-driven decision support. The safe and responsible use of digital technology in cancer care will depend on the establishment of clear regulatory frameworks and best practices.

4.4.2 Implications for Practice and Platform Development

The recurring challenges, including fragmented workflows, poor interoperability between systems, inefficient data management, and the persistent struggle to adopt new technologies, highlight that meaningful digital transformation of MTB practices cannot be achieved without deliberately addressing each of these issues.

This research identifies a number of key factors that are critical for the development, deployment, and successful uptake of digital MTB platforms. A primary requirement is the creation of integrated and interoperable systems that consolidate laboratory, imaging, and clinical data within a single platform. Reducing reliance on fragmented tools such as Word, PowerPoint, and e-mail can significantly enhance both data accuracy and workflow efficiency.

Adoption success strongly depends on usability and user-centered design. Platforms should be intuitive, easy to learn, and aligned with existing clinical workflows to minimize disruption. Incorporating continuous input from healthcare professionals throughout the design and implementation process can further improve system acceptability and long-term sustainability.

Building capacity and providing training are equally essential. Clinicians can better adapt to new technologies, and resistance to change can be reduced, through tailored training programs, ongoing technical support, and clearly defined implementation strategies. The inclusion of dedicated coordination roles, such as tumor board nurse navigators, may further facilitate smooth integration into routine clinical practice.

Clear communication of value is also crucial for promoting adoption. Demonstrating measurable benefits, such as reduced preparation time, improved data accessibility, and enhanced multidisciplinary collaboration, can strengthen stakeholder trust and support investment in digital solutions.

Finally, scalability and adaptability should be prioritized in the design of digital MTB platforms. Systems should be flexible enough to accommodate different institutional contexts, support hybrid meeting formats, and integrate future technological advancements, including AI-driven decision support and immersive virtual reality environments.

Overall, the successful implementation of digital MTB solutions requires not only technological innovation but also careful consideration of workflow integration, user needs, and organizational readiness.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

List of Abbreviations

3D	three-dimensional
AMA	American Medical Association
AI	artificial intelligence
BMFTR	Bundesministerium für Forschung, Technologie und Raumfahrt (German Federal Ministry of Research, Technology, and Space)
CoC	Commission on Cancer
COVID-19	Coronavirus Disease 2019
CT	computed tomography
D	deliverables
DICOM	Digital Imaging and Communications in Medicine
EHR	electronic health record
ELSI	Ethical, Legal, and Social Implications
EMR	electronic medical record
FHIR	Fast Healthcare Interoperability Resources
GLOBOCAN	Global Cancer Observatory
HCP	Healthcare providers
HIS	hospital information system
HIT	health information technology
HMD	head-mounted display
IARC	International Agency for Research on Cancer
IT	information technology
ITB	interdisciplinary tumor board
MCC	multidisciplinary cancer conference
MDM	multidisciplinary management
MDT	multidisciplinary management
MDTM	multidisciplinary team meeting
MR	mixed reality
MRI	magnetic resonance imaging
MR-HNTB	mixed reality head and neck tumor board
MRN	medical record number
MTB	multidisciplinary tumor board
PET	positron emission tomography
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRISMA-ScR	Preferred Reporting Items for Systematic Reviews and Meta-Analyses Scoping Review

RQ	research question
SOP	standard operating procedure
SPICE	setting, perspective, intervention, comparison, evaluation
TB	tumor board
UK	United Kingdom
VR	virtual reality
VR-MTB	virtual reality multidisciplinary tumor board
vMTB	virtual multidisciplinary tumor board
WP	work package
XR	extended reality

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10P-Health: A Conceptual Framework for Continuous, Digitally Enabled Precision Health and Wellness

10P-Health: A Framework for Precision Health and Wellness

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ABSTRACT

Personalized medicine has advanced individualized prevention, diagnosis, and treatment through genomics, multi-omics, and artificial intelligence. Nevertheless, its implementation remains constrained by fragmented data, limited interoperability, episodic care, privacy concerns, and the insufficient use of behavioral, environmental, social, and continuously generated health information. Building on the evolution from P4 to later "P" models, this position paper proposes 10P-Health as a broader conceptual framework for holistic, continuous, individual-centered, and digitally enabled health and wellness.

The framework integrates ten core principles: Predictive, Preventive, Personalized/Precision, Proactive, Participatory, Pertinent, Pervasive, Permanent, Privacy-Preserving, and Platform-Based. Together, these principles connect individualized risk assessment and intervention with individual participation, longitudinal monitoring, contextual relevance, responsible data use, and interoperable digital infrastructure. To translate the concept into practice, the paper presents a layered reference architecture linking multimodal data acquisition, harmonization, secure integration, analytics, decision support, individual engagement, and controlled secondary research.

Real-world adoption requires balancing the framework's principles while addressing technological, operational, ethical, and legal challenges, including data generation and usage, data quality, clinical validation, workflow redesign, professional accountability, consent, equity, reimbursement, and sustainable governance. The paper recommends implementing 10P-Health through defined use cases, stakeholder-led pilots, continuous evaluation, and progressive scaling. It offers a structured direction for transforming advances in digital health and multimodal data into responsible, continuous, and sustainable personalized health and care.

KEYWORDS

10P-Health, precision health, digital health, AI for health, continuity of care

1. Introduction

1.1 Background and Context

Conventional medicine is designed largely around the "average" patient, applying standardized protocols even though individuals differ substantially in how they develop disease and respond to therapy. Personalized medicine departs from this one-size-fits-all model by tailoring prevention, diagnosis, and treatment to each patient's genetic, molecular, environmental, and lifestyle characteristics, so that diagnostic and therapeutic decisions are guided by individual molecular profiling rather than population averages [1,2]. The growing accessibility of multi-omics data spanning genomics, epigenomics, transcriptomics, proteomics, and metabolomics has been central to this shift, since integrating these layers yields a more comprehensive picture of individual health and enables more precise, better-tolerated therapeutic strategies [3].

Personalized medicine has advanced in many areas. In pharmacogenomics, genetic variation in drug metabolism, efficacy, and toxicity informs prescribing in oncology, so that genotype-guided dosing can reduce severe adverse reactions, however routine implementation of such testing is still limited [4]. Oncology remains one of the leading domains, where next-generation sequencing and bioinformatics have made it faster to detect mutations for which targeted agents exist, although incorporating genomic profiles into routine clinical workflows remains difficult [5].

Artificial intelligence is widely expected to enable the next stage of this shift by integrating heterogeneous, multimodal data such as electronic health records, medical imaging, genomics and other omics, environmental exposures, and wearable sensor streams within a single analytical framework [2]. Machine learning and deep learning models can detect intricate, non-linear relationships that span these modalities, strengthening early detection, patient stratification, clinical decision support, and treatment response prediction [2]. Integrating molecular, phenotypic, and environmental data across omics layers is in turn expected to sharpen risk assessment and enable earlier intervention [3].

These advances remain constrained by interdependent barriers. Even setting artificial intelligence (AI) aside, realizing personalized healthcare is hindered by the complexity of integrating data across omics layers, heavy computational demands, high generation costs, and the need for standardization and robust validation in diverse populations [3]. For AI specifically, clinical translation is further limited by fragmented and poorly interoperable data, insufficient real-world validation, algorithmic bias, limited transparency, and privacy concerns [2]. Among these, privacy is especially consequential: the sensitive patient data most valuable for such modeling is typically locked within isolated institutional silos, and regulatory and ethical constraints impede the large-scale centralization on which conventional model training depends [6].

1.2 The Evolution of "P" Concepts in Personalized Medicine

P4 medicine is an early and influential formulation of the reorientation from traditional to personalized care. Its four attributes are predictive, preventive, personalized, and participatory. Hood and Galas [7] articulated it as a shift from reactive care, which waits for illness to appear, toward a preventive and increasingly wellness-oriented model. Their case was framed in concrete benefits: earlier detection, stratification of patients into groups amenable to optimal therapy, fewer adverse drug reactions, better drug target selection, and cheaper clinical trials.

Hood [8] later grounded the same vision in systems medicine, where omics technologies, network models of disease, and blood-based biomarkers make it possible to detect perturbations before symptoms appear. Flores et al. [9] traced P4 to the convergence of three megatrends: systems biology and systems medicine, the digital revolution, and consumers' growing determination to manage their own health, and specified the infrastructure, including personalized data clouds and analytic techniques for deriving actionable knowledge.

Subsequent models preserve this core and extend it along additional dimensions. P5 medicine introduces a psycho-cognitive component. Its proponents argue that a predominantly biological account neglects the manner in which individuals experience illness, cope, and reach decisions [10]. P6 medicine retains this dimension and adds a public one, reframing medical practice as population-based, shared, and open-source [11]. P9 medicine was advanced within a health-information-technology context. It augments the P4 foundation with pervasive, precise, privacy-preserving, protective, and priced-reasonably attributes. In doing so, it incorporates precision medicine considerations together with the infrastructural, security, and affordability requirements of a networked health system [12].

1.3 Problem Statement

Despite the advances described above, several structural limitations continue to constrain the field. The first limitation is data fragmentation. Clinical records, genomic data, and imaging results are typically held by separate institutions under separate governance regimes, with no shared architecture for integration. Data silos therefore remain a structural constraint on any framework that aims to integrate multimodal data.

The second is the limited scope of current clinical applications that mainly focus on biomarker-guided oncology, genomic diagnosis of rare diseases, and selected pharmacogenomic decisions. The third limitation is that care remains episodic rather than continuous. Current health systems are organized around the clinical encounter as the basic unit of care, and depend on it as the main source of individual data, while the use of remote and continuous monitoring, including wearable devices, home-based sensors, and related digital health technologies as a routine source of data between encounters remains behind. Fourth is that personalized medicine today relies mainly on omics and clinical data. Other factors known to influence health outcomes, including environmental exposure, data from the Internet of Things, social media, and behavioral data, and broader social determinants of health, are not utilized in their full capacity in the creation of personalized health solutions.

1.4 Aim, Methodology and Structure of the Paper

This position paper responds to the limitations set out above by proposing the 10P-Health framework, a conceptual extension of the 4P model of personalized medicine. Where the 4P model established the shift from reactive care to predictive, preventive, personalized, and participatory care, 10P-Health reframes that vision around the continuity of care, using digital health technologies and multimodal health data to inform decisions beyond the individual clinical encounter.

This paper pursues two objectives. First, it develops the 10P-Health concept into a scholarly framework, defining its ten principles. Second, it outlines a layered reference architecture that specifies the principal functional requirements for exploiting multimodal data.

Methodologically, the framework was developed through a narrative synthesis of the literature on the evolution of "P" models in personalized medicine (Section 1.2), which was used to further describe the 10P-Health concept originally formulated by Chaltikyan (Section 2.1). Each principle was then examined for the functional requirements it places on data, services, and governance, and these requirements were organized into the layered reference architecture presented in Section 2.2. The framework is intended as a reference for future research and design in personalized health, not as an empirically validated system.

2. The 10P-Health Framework

2.1 Overview

The 10P-Health framework described by Georgi Chaltikyan [13] (G. Chaltikyan, personal communication, November 14, 2019), brings together ten complementary principles that define a continuous, individual-

centered, and digitally enabled model of health. Personalized and Precision form the foundation of the framework. Precision uses molecular, biological, clinical, environmental, and lifestyle data to support risk stratification, disease classification, and treatment selection, whereas personalized extends this approach by adapting care to the individual's psychological, social, environmental, and broader life-context characteristics. Predictive builds on these data to estimate future disease risks, health trajectories, treatment responses, and potential complications before they become clinically evident.

These predictions are translated into action through Preventive, which uses long-term risk forecasts to support actions that reduce the likelihood of future health problems before symptoms develop. Proactive initiates timely and personalized responses to identified risks rather than waiting for disease to emerge or for the individual to seek care. Pertinent focuses on delivering relevant and timely healthcare interventions. This involves real-time data analysis, quick adaptation to changing health conditions, and ensuring that interventions align with the specific needs of the individual or population.

Participatory positions individuals as active partners in their care by involving them in decision-making, health-data contribution, self-management, and care planning. Pervasive extends health support beyond conventional clinical settings by embedding it into everyday life through remote care, ubiquitous technologies, and connected devices. Permanent adds a longitudinal dimension by maintaining continuity of health information, monitoring, and support across the life course, healthcare providers, care settings, and clinical episodes.

These principles require both technological coordination and responsible data governance. Privacy-Preserving protects personal health information throughout its collection, storage, analysis, and exchange through data minimization, secure computation, access control, transparency, and accountable governance. Platform-Based provides the coordinating foundation through which heterogeneous data sources, analytical services, digital technologies, care processes, and stakeholders can interact within an interoperable, modular, and individual-centered health ecosystem.

Although several principles are closely related, each has a distinct operational role (Table 1). Predictive, Preventive, Proactive, and Pertinent form a sequence rather than overlapping labels: Predictive estimates risk, Preventive targets the long-term reduction of that risk, Proactive determines when action is initiated without waiting for the individual to seek care, and Pertinent adapts the content of that action to the individual's current context. Similarly, Pervasive and Permanent describe two different dimensions of continuity: Pervasive concerns where health support is available, across everyday settings, whereas Permanent concerns how long it is maintained, across the life course and successive care episodes.

Principle	Distinct operational role	Main output
Personalized/ Precision	Tailors risk stratification, classification, and care to the individual's biological and life-context characteristics	Individual-specific stratification and care options
Predictive	Estimates future risks, health trajectories, and treatment responses	Risk estimates and forecasts
Preventive	Reduces the long-term likelihood of disease before symptoms develop	Preventive options and goals
Proactive	Initiates timely action on identified risks without waiting for the individual to seek care	Timely prompts and referrals
Participatory	Involves the individual as an active partner in decisions and self-management	Shared decisions and self-management plans
Pertinent	Delivers relevant and timely interventions that adapt to changing health conditions and to the specific needs of the individual or population	Relevant, context-adapted interventions
Pervasive	Extends health support across everyday settings (where support is available)	Support outside clinical settings
Permanent	Maintains continuity of information and support over time (how long support is maintained)	Life-course health record and follow-up
Privacy-Preserving	Protects personal health information throughout its collection, analysis, and exchange	Minimum authorized data and auditable use
Platform-Based	Enables interoperable, modular interaction of data, services, and stakeholders	Interoperable, replaceable services

Table 1: Distinct operational roles of the ten 10P-Health principles.

Realizing this vision depends on advances in data analytics and on the large volumes of information generated by sensors and Internet of Things devices outside traditional clinical encounters. Such data may be produced continuously across smart homes, hospital-at-home programs, smart cities, and connected hospital environments such as intensive care units. The framework integrates these real-world data streams with clinical and genomic information to create a unified and continuously updated view of the individual. In this way, personalized healthcare can become part of everyday life rather than remain confined to episodic clinical visits, with the broader aim of improving quality of life and extending healthy life expectancy.

2.2 Implications and Applications

10P-Health is a paradigm for organizing health and wellness. At its center is the individual, who serves as the organizing point around which health information, analytical capabilities, preventive support, and decisions concerning data use are coordinated. This individual-centered orientation can be embodied in a personal health companion, a conceptual individual-facing function through which a person connects relevant sources of health information and manages which data can be used, for what purpose, and for how long.

The companion is intended to provide continuity across everyday life and changes in health status. It can support different use cases such as understanding personal measurements and longitudinal trends, obtaining health information, exploring future risks, considering preventive options, setting goals, and recognizing when professional assessment may be required. These needs can use different combinations of data analysis, health-domain knowledge, behavior support, and professional input.

Individuals can interact with the framework through different digital interfaces, including conversational interfaces enabled by large language models. Such interfaces provide an accessible point of interaction by interpreting the individual's request and communicating it to the coordination and orchestration function, which identifies the relevant information and services. Relevant multimodal personal health data may originate from wearables, home-based sensors, mobile and consumer devices, self-reported information, personal or electronic health records, healthcare providers, laboratories, medical-imaging systems, genomic and other omics repositories, and environmental, behavioral, psychological, and social sources. Validated, use-case-specific analytical models process the relevant multimodal data to generate risk estimates, forecasts, classifications, or other health-related outputs, while the personalized health companion communicates the results in understandable language.

A coordination and orchestration function links the companion to these distributed data sources to analytical, knowledge-based, and behavior-support services. Based on the individual's request, permissions, and intended purpose, it identifies the appropriate services and the minimum authorized information required. Interoperability, data quality, privacy, and governance operate across these connections. Information should be technically and semantically interpretable and accompanied, where relevant, by details concerning its source, timing, completeness, quality, and permitted use. This is particularly relevant for data from consumer wearables and home-based sensors, which are affected by measurement error, motion artefacts, and missing data arising, for example, from non-wear or device charging [14]. Such data should therefore undergo quality control, including the handling of missing values and the flagging or filtering of implausible measurements, before they are made available to analytical services. Access should remain proportionate to the intended purpose and subject to appropriate requirements concerning identity, authorization, consent, purpose limitation, data minimization, transparency, auditability, and accountability.

The framework relies on modular and purpose-specific services rather than a single model or service intended to address every health need. Different conditions, populations, prediction periods, and data combinations may require different analytical models. Each service should therefore have a defined purpose, required inputs, validation status, limitations, and conditions of use. Models and services should also be governed, monitored, and applied only within their intended scope. This modular structure

allows individual services to be updated or replaced without redefining the wider 10P-Health paradigm.

Depending on the legal, organizational, privacy, and governance requirements of the context, multimodal model development may use governed central environments, distributed analysis, federated methods, or hybrid arrangements. The selection of a specific technical architecture for developing and applying multimodal models across distributed data sources lies beyond the scope of this conceptual framework. Before analytical outputs are communicated to the individual, they should be assessed for data sufficiency, evidential grounding, relevance, consistency, uncertainty, and alignment with the intended use. A predictive multimodal model may estimate a risk or future trajectory, but translating that estimate into an appropriate response requires health knowledge, safety considerations, individual preferences, and, where necessary, professional judgement. The companion can therefore explain the result, the factors that contributed to it, the limitations of the available information, the degree of uncertainty, and the possible next steps.

Beyond presenting information, the companion may help individuals translate insights into action by setting meaningful goals, selecting feasible preventive steps, and monitoring progress. With appropriate consent and governance, relevant goals and prior actions can be retained to support continuity while preserving individual autonomy. The functions described above are organized into the layered conceptual reference architecture shown in Figure 1.

Healthcare professionals and caregivers remain important within this model. Their involvement occurs through controlled access when required. Selected information may be shared for preventive assessment, diagnosis, treatment, emergency care, or shared decision-making. When a professional assessment is necessary, the companion should facilitate an appropriate connection to healthcare services. For secondary purposes, individuals can choose to contribute by giving permission for the use of selected data to research, public-health, or multimodal model development activities under legal, ethical, and governance arrangements.

An illustrative scenario demonstrates how these functions may interact. An individual may ask how their biological, clinical, behavioral, environmental, or social circumstances influence their risk of developing a condition and what actions could reduce that risk. The companion would interpret the request, identify an appropriate validated model and supporting services, and determine which authorized information is required. Relevant data could be accessed or analyzed where they are held, and the resulting forecast would be reviewed for quality, relevance, and uncertainty before being explained with its contributing factors, limitations, and possible preventive options. Box 1 illustrates these interactions step by step across the reference architecture.

Box 1. Illustrative walkthrough across the reference architecture

1. Distributed data sources. An individual uses a wearable device and home-based sensors that record physiological and activity data. They have consented to these data being linked with their laboratory results and the records held by their healthcare provider.

2. Data access and interoperability. Incoming sensor data are checked for gaps and implausible values, labelled with their source and time, and harmonized with laboratory and record data using common standards. Only the data streams covered by the individual's current consent are made available.

3. Coordination and orchestration. When the individual asks the companion why a monitored measure has recently changed, or when a sustained deviation from their personal baseline is detected, the coordination function identifies a validated, use-case-specific risk model and requests only the minimum data it requires.

4. Validated services. The model is applied where the data are held and returns a risk estimate together with its uncertainty and contributing factors, which may include changes in physiological measurements, physical activity, or other behavioral and environmental factors.

5. Personal AI health companion. The companion explains the result in understandable language, states its limitations, and suggests feasible preventive options, such as changes in physical activity or daily routines, while recording the goals the individual agrees to pursue.

6. Professional services. If the estimate exceeds the level defined for the model's intended use, or persists despite the agreed actions, the case is escalated or referred to a healthcare provider or professional, as appropriate. With the individual's permission, a summary is shared with that provider, who confirms or rejects the finding through an appropriate assessment and determines any further care. The outcome is returned to the companion and added to the individual's longitudinal record.

This example is illustrative only. It has not been implemented or validated.

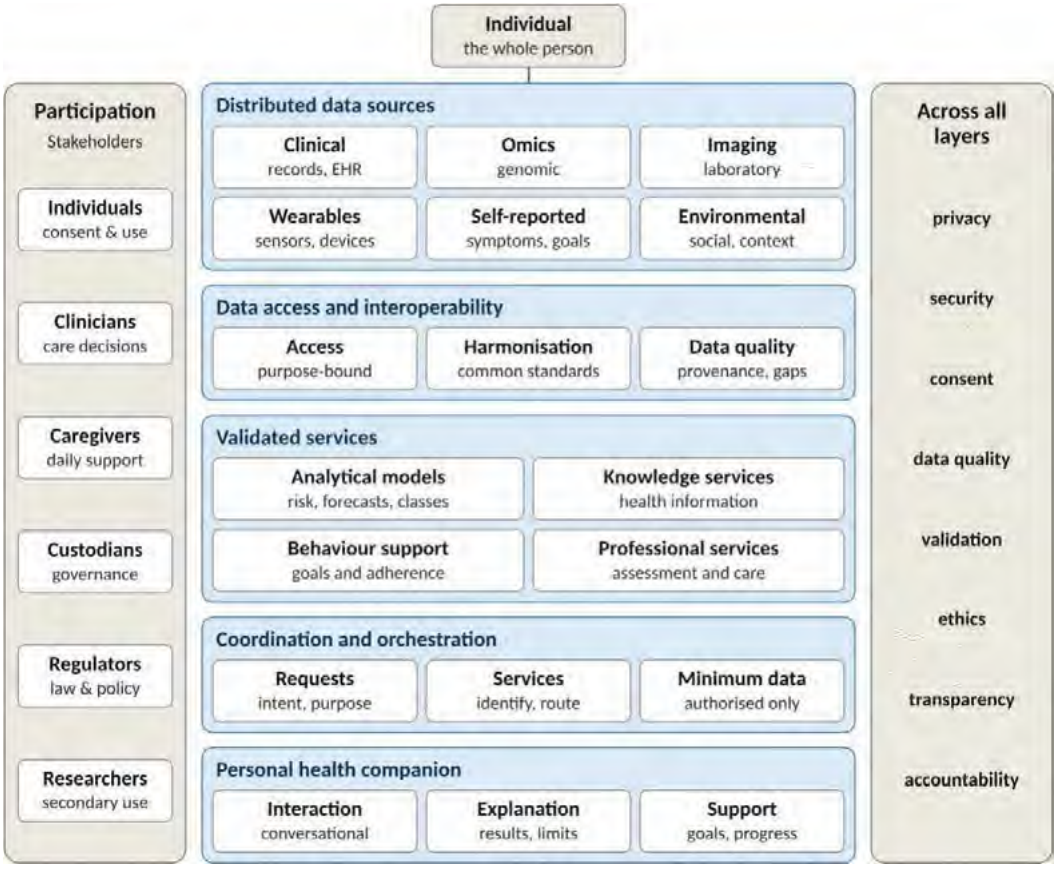


Figure 1. Conceptual architecture of the 10P-Health framework: Multimodal data from the individual are continuously acquired, harmonized through interoperability standards, and securely integrated within the 10P-Health platform to support a unified longitudinal health record, analytics, decision support, individual-facing applications, and research. Stakeholder participation, governance, and privacy-preserving design operate across all layers.

3. Challenges to Real-World Adoption of 10P-Health

Adopting 10P-Health in practice requires translating its ten principles into coordinated clinical and organizational processes instead of treating them as independent objectives. Tensions may arise between principles, for example, pervasive and permanent monitoring may be deemed conflicting with privacy-preserving aspects, while proactive intervention may increase unnecessary testing or overmedicalization. Participatory care must also be balanced with professional responsibility and individual preferences.

Technologically, adoption depends on the reliable integration of longitudinal clinical, genomic, behavioral, environmental, and sensor-generated data. Key barriers include limited interoperability, variable data quality, algorithmic bias, and insufficient external validation across diverse populations and care settings.

Operationally, healthcare organizations must redesign workflows, define responsibilities, train professionals, establish reimbursement mechanisms, and secure long-term funding. Clinician resistance, individual digital literacy differences, additional workload, and unclear ownership of continuous monitoring may further limit routine adoption. Realizing this vision also depends on sustained collaboration across stakeholders, regulators, healthcare providers, payers, technology developers, researchers, and individuals whose aligned incentives, shared governance, and coordinated standards are needed to move the framework from concept to routine practice.

Legally, the framework raises questions concerning continuous consent, data protection, secondary data use, cross-institutional and cross-border exchange, and liability for algorithm-supported decisions. Clear governance is therefore required to determine who may access data, who is accountable for recommendations, and how individual rights are preserved throughout lifelong data use. Because permanent monitoring may extend over many years, consent should be dynamic and granular rather than a single, all-or-nothing decision, allowing individuals to set different preferences for different data streams and uses and to modify these preferences over time [15]. For example, an individual could withdraw consent for a specific wearable or home-sensor stream while maintaining clinicians' access to their health records. In the European context, such arrangements must comply with the General Data Protection Regulation.

Psychological and behavioral effects also require particular consideration. Continuous monitoring and repeated communication of possible future risks may increase anxiety, encourage excessive attention to normal physiological variation, or create a sense of being continuously medically evaluated. False-positive alerts may further increase anxiety and unnecessary use of healthcare services, whereas false reassurance may delay appropriate professional assessment. In addition, wearable-based assessment of stress, anxiety, and depression remains limited by small study populations, short follow-up periods, and inconsistent validation, raising concerns about the reliability of psychological predictions.

4. Conclusion and Recommendations

The 10P-Health framework extends personalized medicine beyond isolated genomic applications and episodic clinical encounters toward a holistic, continuous, multimodal, participatory, and digitally enabled model of health. Its ten principles connect personalization, prediction, prevention, participation, pertinence, proactivity, pervasiveness, permanence, privacy preservation, and platform-based delivery within a single conceptual framework. The central position of this paper is that these principles should not be implemented as separate technological functions, but as interdependent requirements for designing the health and wellness journey of an individual across settings, providers, and stages of life. Realizing the 10P-Health paradigm does not necessarily entail immediate implementation at a large scale. Adoption can begin with a clearly defined clinical or population-health use case, such as remote chronic-disease monitoring, hospital-at-home care, preventive risk assessment, or personalized treatment support. The relevant 10P principles can then be translated into measurable clinical, technical, regulatory, ethical, and operational requirements. Organizations can identify the necessary data sources, establish interoperability and governance arrangements, define professional and individual responsibilities, and select an appropriate centralized, federated, or hybrid architecture.

The framework can subsequently be introduced through a limited pilot that integrates selected clinical and individual-generated data into existing workflows. Analytical outputs should be externally validated, clinically interpretable, and evaluated for safety, utility, equity, privacy, individual experience, workload, and cost. Individuals, clinicians, regulators, data custodians, payers, researchers, and technology providers should be involved throughout the design and evaluation, rather than consulted only after implementation. Successful pilots may then be expanded progressively across user groups, organizations, regions, or cross-border networks, while preserving common interoperability, accountability, and privacy requirements.

Implementation should therefore be viewed as an iterative learning process rather than a single technology deployment. Throughout implementation, data quality, analytical model performance, health outcomes, unintended consequences, cybersecurity risks, and changes in individual preferences should be continuously monitored. Evidence generated through routine care and controlled secondary research can inform the refinement of the implemented services and applications.

Future research should develop measurable indicators for each principle and evaluate whether different implementations improve health outcomes, quality of life, continuity of care, individual participation, equity, and healthy life expectancy. The contribution of the 10P-Health concept is therefore not a fixed technical solution, but a structured direction for translating advances in digital health, multimodal data,

and artificial intelligence into responsible and sustainable personalized healthcare.

Declarations

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Public Readiness for a Personalized Digital Health Platform in Bavaria (10P-Health): A Cross-Sectional Survey of Operational, Legal, Technological, and Stakeholder Determinants of Perceived Feasibility

Public Readiness for 10P-Health Platform in Bavaria

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ABSTRACT

Background: Digital health technologies and artificial intelligence (AI) are shifting healthcare from reactive treatment toward predictive and personalized care. The 10P-Health framework extends earlier P-models through ten principles: Predictive, Preventive, Personalized/Precision, Participatory, Pertinent, Proactive, Privacy-preserving, Pervasive, Permanent, and Platform-based. Public readiness for such a framework in Bavaria has not been established.

Objective: This study assessed public readiness for the 10P-Health framework in Bavaria and examined whether operational readiness (OR), legal and regulatory requirements (LRR), stakeholder engagement (SE), and technological infrastructure (TI) predict its perceived feasibility.

Methods: A cross-sectional survey of 200 adult residents of Bavaria was conducted using an online questionnaire. All constructs were measured with five-point Likert scales. Data were analyzed with descriptive statistics, reliability analysis, principal component analysis, Pearson correlations, and multiple linear regression.

Results: Respondents were predominantly young and well-educated, and 77.5% had previously used a digital health platform, medical device, or health-related application. All constructs showed acceptable internal consistency (Cronbach's alpha = .706–.768). Perceived feasibility correlated significantly with all four predictors. The regression model explained 57.7% of the variance in perceived feasibility. TI (β = .402, $p < .001$), OR (β =.330, $p < .001$), and SE (β = .207, p = .001) were significant predictors, whereas LRR was not (β = .029, p = .614). Resource adequacy and provider preparedness received the lowest ratings.

Conclusions: The findings indicate moderate readiness among a predominantly young, highly educated, and digitally experienced sample. Perceived feasibility was associated primarily with technological infrastructure, operational readiness, and stakeholder engagement, whereas legal requirements appeared to function as a background condition rather than a direct driver.

KEYWORDS

AI in health, personalized medicine, patient attitudes, public readiness, 10P-Health

1. Introduction

1.1. Background

Healthcare is shifting from reactive treatment toward proactive, predictive, and personalized care, driven by advances in artificial intelligence (AI) and digital health [1,2]. This transition has been shaped by the gradual evolution of personalized-medicine paradigms. The P4 medicine model presented predictive, preventive, personalized, and participatory, articulated by Hood and Galas [3]. Subsequent models proposed a P5 medicine that adds the psycho-cognitive dimension proposed by Gorini and Pravettoni [4], and the model was later broadened to a 6P framework incorporating the additional dimension of public health [5]. The framework was subsequently expanded to a P9 concept of healthcare, encompassing personalized, predictive, preventive, participatory, pervasive, precise, privacy-preserving, protective, and priced-reasonably dimensions [6].

Building on this trajectory, Chaltikyan [7] (G. Chaltikyan, personal communication, November 14, 2019) describes 10P-Health, which extends earlier P-models through ten principles: Predictive, Preventive, Personalized/Precision, Participatory, Pertinent, Proactive, Privacy-preserving, Pervasive, Permanent, and Platform-based. The 10P-Health framework reflects the convergence of personalized medicine with digital health, big data, and AI. Rather than prescribing a fixed implementation pathway, it emphasizes the integration of multimodal data, the use of digital health applications, continuous monitoring, the application of AI and predictive analytics. Its orientation remains patient-centered, seeking to enable more effective disease management and timely interventions while stressing on continuity of care beyond clinical encounter, patient inclusion, interoperability, and platform-based infrastructure that can support long-term, precision-oriented care.

1.2 The Bavarian Context

Despite global progress, healthcare systems have faced difficulties in adopting data-intensive and AI-driven models, particularly in relation to technological readiness, regulatory constraints, and infrastructure [8]. Bavaria is one of the most financially developed regions in Germany [9], and its health and care economy represents a major share of the state's economic output and employment [10]. Bavarian institutions have access to high-quality patient care and advanced medical research, but the transformation toward personalized interventions, real-time monitoring, and AI-driven analytics is still in its early stages.

Operational readiness in this context reflects preparedness to scale up digital health platforms, data-sharing mechanisms, and AI-driven health technology [11]. Effective integration of a 10P-Health framework requires a robust technical infrastructure capable of integrating multimodal health data sources, including omics, internet of things (IoT), imaging, and electronic health records (EHR). Data silos and technological barriers often fragment systems and hinder timely, personalized care [12]. Training practitioners to work with AI-based decision tools is important because AI complements medical expertise [13], and improving patient digital literacy is equally necessary for informed engagement with digital tools [14]. Without fundamental digital competencies, patients struggle to benefit from personalized technologies, which can widen health disparities [15].

Bavaria's digital health transition is also shaped by a multi-layered regulatory environment. AI-driven healthcare must respect patient rights, ethics, and data protection law [16]. The European Health Data

Space (EHDS) aims to foster secure health data exchange across European Union member states while empowering patients with greater control over their data [17], yet its integration requires navigation of overlapping frameworks including the General Data Protection Regulation (GDPR), the Federal Data Protection Act (BDSG), and the Bavarian Data Protection Act (BayDSG). Additional national frameworks relevant to digital health include the Digital Act (DigiG), the Health Data Use Act (GDNG), the Digital Healthcare Act (DVG), and the Medical Device Regulation (MDR). Strict privacy safeguards such as those in the GDPR are required to balance patient confidentiality with data accessibility. At the same time, Bavaria supports AI in healthcare through initiatives within the High-Tech Agenda Bavaria and centers such as BayernKI, which promote digital health platforms, telemedicine, and AI-powered diagnostics.

1.3. Problem Statement

Personalized health offers advantages that elevate patients' overall care. Yet realizing such an approach and adopting a comprehensive model such as the 10P-Health framework in the Bavarian healthcare system remains uncertain. This uncertainty arises from concerns about technological infrastructure, stakeholder engagement, regulatory and legal compliance, and operational readiness. Integrating personalized health platforms requires investment in digital systems, workforce training, and AI-powered solutions to ensure smooth adoption; without a clear assessment of these elements, resistance to change, data silos, and inefficiencies could hinder implementation. Complex regulations add further difficulty, as a personalized platform must meet strict legal requirements while maintaining data security and patient privacy. Stakeholder engagement is equally important, since issues of trust, acceptance, and awareness of AI-based solutions have produced resistance to change. It also remains unclear whether Bavaria's technical capabilities are sufficient to support real-time tracking, system integration, and large-scale, device-agnostic health data.

Patients' perceptions, trust, and attitudes toward AI-based health platforms need to be assessed, as these factors strongly influence their adoption and sustained use. Understanding these perceptions is therefore necessary to inform an ethically sound, legally compliant, and patient-centered digital transition. This study addresses these gaps by using a quantitative survey to evaluate public readiness and to examine the factors associated with the perceived feasibility of implementing a personalized 10P-Health framework in Bavaria.

1.4 Aim and Objectives

This study assessed the feasibility of implementing the 10P-Health framework in Bavaria from the perspective of adult residents, evaluating four factors: operational readiness, legal and regulatory requirements, stakeholder engagement, and technological infrastructure. The objectives were:
1 – Assess the level of operational readiness required, including infrastructure, workforce, and resource availability in Bavaria.
2 – Identify perceptions of the legal and regulatory requirements related to healthcare data, patient privacy, and adherence to Bavarian, German, and EU laws.
3 – Evaluate the role of stakeholder engagement.
4 – Investigate perceptions of the technological infrastructure required to support the scalability in Bavaria.

2. Methods

2.1 Study Design

This study used a quantitative, cross-sectional survey design. The survey collected statistically analyzable, comparable, and measurable data on patient attitudes toward digital health technologies, AI-driven care, and data sharing.

2.2 Setting and Participants

The study was conducted in the German federal state of Bavaria. Eligible participants were adults (18 years or older) residing in Bavaria, representing a range of digital health experiences. On the consent page, respondents confirmed that they were at least 18 years old before starting the questionnaire, and residence was recorded through a required question on region of residence within Bavaria. The number of completed responses obtained was 200, with no missing values on any analyzed variable, because every questionnaire item required an answer before the form could be submitted. The survey administration period was June until August 2025.

2.3 Recruitment

Participants were recruited through non-probability convenience sampling. Data were collected through an anonymous, bilingual (German and English) questionnaire hosted on Google Forms, which took about 10 minutes to complete and required no login or personal details. To broaden outreach beyond online channels and to include people with different educational backgrounds and levels of digital skill, a bilingual flyer in English and German was developed, printed, and handed out in person in selected regions of Bavaria, specifically Pfarrkirchen, Munich, and Erlangen. The flyer carried a QR code linking to the questionnaire, and people who were less familiar with digital tools could complete the questionnaire with assistance from a member of the research team. Internal distribution was additionally facilitated through a professional network in Munich. Recruitment was further supported by email communication with multiple organizations, including elderly care facilities and community-based associations, inviting their members to participate. Despite these measures, the final sample remained predominantly young and highly educated (Section 3.1); the implications are discussed in Section 5.
Because the questionnaire was distributed through an open link, printed flyers, and partner organizations, the number of people who received the invitation is unknown, and a response rate could not be calculated. Google Forms records only submitted responses, so partially completed questionnaires were not captured. A total of 200 complete responses were received during the survey period.

2.4 Questionnaire and Measures

All 21 construct items were developed de novo for this study, based on the literature on personalized medicine, digital health readiness, data protection, and stakeholder engagement reviewed in Section 1, rather than adapted from existing validated scales. Responses were measured as levels of agreement or disagreement with a series of statements, using five-point Likert scales ranging from 1 to 5, with higher values indicating stronger agreement.

The instrument comprised three parts. The first part collected demographic characteristics: age group, gender, highest level of education, and region of residence within Bavaria. The second part assessed digital health background: self-rated familiarity with digital health technologies, previous use of a digital health platform, medical device, or health-related application, the presence of chronic health conditions, and frequency of use of six categories of digital health services or tools (telemedicine consultations or virtual doctor visits, fitness and wellness applications, remote monitoring devices or applications, medication reminders or appointment scheduling tools, patient portals, and online symptom checkers or chat-based health services).

The third part measured five constructs using 21 Likert-scale items. Operational Readiness (OR) comprised four items covering the adequacy of system resources such as funding, trained staff, and technical infrastructure; the monitoring and improvement of digital health services; the training and comfort of healthcare professionals with digital tools; and willingness to pay a reasonable amount for personalized digital health services.

Legal and Regulatory Requirements (LRR) comprised four items covering trust that certified platforms protect data privacy and security; clarity of information about how health data is collected, used, and shared; ease of giving or withdrawing consent; and confidence in current laws and regulations such as the GDPR.

Stakeholder Engagement (SE) comprised four items covering whether digital health tools are designed with patients' needs in mind and incorporate patient feedback; whether patients and citizens should be consulted when new digital health services are developed; trust in digital health systems and AI-generated recommendations when supervised by medical professionals; and whether digital health services should be accessible and inclusive regardless of income, disability, language, or digital skills.

Technological Infrastructure (TI) comprises four items covering seamless sharing of health records among treating doctors or clinics; reliable access to internet or mobile networks; smooth interoperability of digital systems and applications used in healthcare; and openness to digital tools that use AI and analytics to help predict or prevent health problems.

Feasibility of Implementing a Health Platform (FIHP) comprises five items covering whether using a personalized digital health platform seems practical and achievable; whether such a platform could be integrated into daily routine without major disruption; whether the healthcare providers and institutions used by the respondent are prepared to support personalized digital health services; whether certified personalized platforms should be supported long-term; and whether the benefits of a personalized platform will outweigh the costs and risks. FIHP was treated as the dependent variable. OR, LRR, SE, and TI were treated as independent variables, and the construct scores were computed as the mean of their constituent items, with each item weighted equally.

2.5 Ethical Considerations

All participants provided informed consent prior to data collection, ensuring their awareness of the purpose and procedures of the study and of their right to withdraw at any time without consequence. Privacy and anonymity were maintained, with survey responses securely stored and anonymized to prevent the identification of participants. The research complied with the GDPR and other applicable data protection laws. Data integrity and researcher neutrality were maintained by avoiding leading questions and any form of pressure on respondents.

2.6 Statistical Analysis

Data were analyzed using IBM SPSS Statistics (Version 31.0.0.0; IBM Corp.) [18]. Demographic and digital health background variables were summarized using frequencies and percentages. Construct items were summarized using means, standard deviations, minimum, and maximum values.

The distribution of each construct item was examined using the Kolmogorov-Smirnov test with Lilliefors significance correction. Internal consistency was assessed for each construct using Cronbach's alpha, with .70 applied as the acceptable threshold. The suitability of the data for factor analysis was examined using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. Principal component analysis with varimax rotation and Kaiser normalization was then performed on the 21 construct items, with a fixed five-factor solution. Composite reliability (CR) and average variance extracted (AVE) were calculated for each construct, with .50 applied as the benchmark for AVE.

Relationships among constructs were examined using Pearson correlation coefficients with two-tailed significance tests. Multiple linear regression was conducted with FIHP as the dependent variable and OR, LRR, SE, and TI entered simultaneously. Multicollinearity was assessed with tolerance and variance inflation factor (VIF) values derived from the correlations among the predictors (Table 9), with VIF values below 5 taken to indicate no problematic collinearity. Although the item distributions departed from normality, the normality assumption of linear regression concerns the residuals rather than the individual items, and least-squares estimates and their confidence intervals remain valid without normally distributed data in sufficiently large samples, often fewer than 100 observations [19]. Ordinary least-squares regression was therefore retained, and 95% confidence intervals for the regression coefficients are reported. Statistical significance was set at $p < .05$.

3. Results

3.1 Participant Characteristics

Table 1 presents respondents' demographic characteristics. Most respondents were under 35 years old, including 50.0% aged 25–34 and 16.5% under 25. The remaining respondents were aged 35–44 (16.0%), 45–54 (8.5%), or 55 and above (9.0%). Females accounted for 59.5% of the sample, males for 40.0%, and 0.5% preferred not to state their gender. Regarding education, 38.0% held a Master's degree or equivalent and 33.0% held a Bachelor's degree, while 14.5% reported a high-school diploma, 10.5% an apprenticeship or technical certificate, and 3.0% a doctorate. Geographically, 43.5% of respondents were located in Lower Bavaria and 36.0% in Upper Bavaria, with the remaining regions each accounting for 7.0% or less.

Characteristic	Category	n	%
Age group	Under 25	33	16.5
	25–34 years	100	50.0
	35–44 years	32	16.0
	45–54 years	17	8.5
	55 years and above	18	9.0
Gender	Female	119	59.5
	Male	80	40.0
	Prefer not to say	1	0.5
Highest level of education	High-school diploma	29	14.5
	Apprenticeship or technical certificate	21	10.5
	Bachelor's degree	66	33.0
	Master's or equivalent	76	38.0
	Doctorate / PhD / MD	6	3.0
	Prefer not to say	2	1.0
Region in Bavaria	Lower Bavaria	87	43.5
	Upper Bavaria	72	36.0
	Upper Palatinate	14	7.0
	Middle Franconia	10	5.0
	Lower Franconia	7	3.5
	Swabia	7	3.5
	Upper Franconia	3	1.5

Table 1: Demographic Characteristics of Survey Respondents (N = 200).

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3.2 Digital Health Background and Service Use

Self-rated familiarity with digital health technologies and prior use of digital health services are presented in Table 2. Of the respondents, 34.0% reported being somewhat familiar and 17.5% very familiar with digital health technologies, while 25.0% were neutral, 17.0% slightly familiar, and 6.5% not familiar at all. Previous use of a digital health platform, medical device, or health-related application was reported by 77.5% of respondents. Chronic health conditions were reported by 28.5% of respondents.
Frequency of use varied across service types (Table 2). Fitness and wellness applications showed the highest engagement, with 34.5% of respondents using them regularly and 23.5% often, and only 15.5% never using them. Telemedicine consultations showed limited adoption, with 47.5% never using them

and 2.0% using them regularly. Remote monitoring devices or applications were never used by 54.5% of respondents, and medication reminders or appointment scheduling tools by 44.5%. Patient portals and online symptom checkers were never used by 33.0% and 40.0% of respondents, respectively.

Item	Category	n	%
Familiarity with digital health technologies	Not familiar at all	13	6.5
	Slightly familiar	34	17.0
	Neutral	50	25.0
	Somewhat familiar	68	34.0
	Very familiar	35	17.5
Ever used a digital health platform, medical device, or application	No	45	22.5
	Yes	155	77.5
Chronic health condition	No	143	71.5
	Yes	57	28.5
Telemedicine consultations or virtual doctor	Never	95	47.5
	Rarely	49	24.5
	Sometimes	37	18.5
	Often	15	7.5
	Regularly	4	2.0
Fitness and wellness apps	Never	31	15.5
	Rarely	24	12.0
	Sometimes	29	14.5
	Often	47	23.5
	Regularly	69	34.5
Remote monitoring devices/apps	Never	109	54.5
	Rarely	43	21.5
	Sometimes	27	13.5
	Often	13	6.5
	Regularly	8	4.0
Medication reminders or appointment scheduling tools	Never	89	44.5
	Rarely	32	16.0
	Sometimes	30	15.0
	Often	19	9.5
	Regularly	30	15.0
Patient portals	Never	66	33.0
	Rarely	58	29.0
	Sometimes	39	19.5
	Often	22	11.0
	Regularly	15	7.5
Online symptom checkers or chat-based health services	Never	80	40.0
	Rarely	49	24.5
	Sometimes	31	15.5
	Often	21	10.5
	Regularly	19	9.5

Table 2: Familiarity With Digital Health Technologies and Frequency of Use of Digital Health Services (N = 200).

3.3 Descriptive Statistics for Construct Items

Item-level descriptive statistics are presented in Table 3. All 21 items used the full response range from 1 to 5. Within Operational Readiness, the adequacy of system resources received the lowest mean of all items (M = 2.73, SD = 0.84), followed by the training and comfort of healthcare professionals with digital tools (M = 2.97, SD = 1.02). Within Legal and Regulatory Requirements, item means ranged from 3.15 (SD = 1.25) for clarity of information about data collection and use to 3.41 (SD = 1.21) for trust in certified platforms. Within Stakeholder Engagement, accessibility and inclusiveness received the highest mean of all items (M = 4.58, SD = 0.80), followed by consultation of patients and citizens (M = 4.25, SD = 0.93). Within Technological Infrastructure, item means ranged from 3.97 (SD = 1.14) to 4.28 (SD = 0.95). Within Feasibility of Implementing a Health Platform, provider preparedness received a mean of 2.75 (SD = 0.94), while long-term support of certified platforms received a mean of 4.20 (SD = 0.88).

Construct	Item	Min	Max	M	SD
OR	The Bavarian healthcare system has enough resources, such as funding, trained staff, and technical infrastructure	1	5	2.73	0.84
	Digital health services will be regularly monitored and improved to ensure quality	1	5	3.20	0.96
	Healthcare professionals I interact with are well trained and comfortable using digital health tools	1	5	2.97	1.02
	I am willing to pay a reasonable amount for personalized digital health services that clearly benefit my health care	1	5	3.26	1.17
LRR	I trust that certified digital health platforms will protect my data privacy and security	1	5	3.41	1.21
	I am clearly informed about how my health data is collected, used, and shared	1	5	3.15	1.25
	When I use digital health apps or platforms, I can easily give or withdraw my consent	1	5	3.39	1.04
	Current laws and regulations (e.g., GDPR) protect my rights in digital healthcare	1	5	3.37	0.99
SE	Digital health tools are designed with patients' needs in mind and incorporate patient feedback	1	5	3.11	0.94
	Patients and citizens should be consulted when new digital health services are developed	1	5	4.25	0.93
	I trust digital health systems and AI-generated health recommendations when supervised by medical professionals	1	5	3.62	1.09
	Digital health services should be accessible and inclusive, regardless of income, disability, or language	1	5	4.58	0.80
TI	My health records should be shared seamlessly among the doctors or clinics involved in my care	1	5	4.13	1.07
	I have reliable access to internet or mobile networks needed to use digital health services	1	5	4.28	0.95
	Digital systems and apps used in healthcare should work smoothly together	1	5	4.17	1.08
	I am open to digital tools that use AI and analytics to help predict or prevent health problems	1	5	3.97	1.14
FIHP	Using a personalized digital health platform for my own care seems practical and achievable	1	5	3.77	1.06
	I could integrate such a platform into my routine without major disruption	1	5	3.86	0.90
	The healthcare providers and institutions I use are prepared to support personalized digital health services	1	5	2.75	0.94
	Certified personalized digital health platforms should be supported long-term	1	5	4.20	0.88
	The benefits of a personalized digital health platform will outweigh the costs and risks	1	5	3.65	0.94

Table 3: Descriptive Statistics for Construct Items (N = 200).

Note. OR = Operational Readiness; LRR = Legal and Regulatory Requirements; SE = Stakeholder Engagement; TI = Technological Infrastructure; FIHP = Feasibility of Implementing a Health Platform.

Construct-level scores are presented in Table 4. TI recorded the highest mean (M = 4.14, SD = 0.81), followed by SE (M = 3.89, SD = 0.64), FIHP (M = 3.64, SD = 0.68), LRR (M = 3.33, SD = 0.85), and OR (M = 3.04, SD = 0.62).

Construct	Min	Max	M	SD
Operational Readiness (OR)	1.50	5.00	3.04	0.62
Legal and Regulatory Requirements (LRR)	1.00	5.00	3.33	0.85
Stakeholder Engagement (SE)	1.75	5.00	3.89	0.64
Technological Infrastructure (TI)	1.25	5.00	4.14	0.81
Feasibility of Implementing a Health Platform (FIHP)	1.20	5.00	3.64	0.68

Table 4: Descriptive Statistics for Construct Scores (N = 200).

3.4 Normality

Results of the Kolmogorov-Smirnov test are presented in Table 5. All 21 items deviated significantly from a normal distribution ($p < .001$ in every case). Test statistics ranged from 0.169 to 0.261 for the OR and LRR items, from 0.211 to 0.429 for the SE items, from 0.237 to 0.315 for the TI items, and from 0.210 to 0.270 for the FIHP items. The largest deviation was observed for SE4 (0.429).

Item	Statistic	df	Sig.	Item	Statistic	df	Sig.
OR1	0.261	200	< .001	SE3	0.281	200	< .001
OR2	0.225	200	< .001	SE4	0.429	200	< .001
OR3	0.194	200	< .001	TI1	0.274	200	< .001
OR4	0.242	200	< .001	TI2	0.315	200	< .001
LRR1	0.223	200	< .001	TI3	0.298	200	< .001
LRR2	0.169	200	< .001	TI4	0.237	200	< .001
LRR3	0.186	200	< .001	FIHP1	0.241	200	< .001
LRR4	0.192	200	< .001	FIHP2	0.262	200	< .001
SE1	0.211	200	< .001	FIHP3	0.220	200	< .001
SE2	0.285	200	< .001	FIHP4	0.270	200	< .001
FIHP5	0.210	200	< .001				

Table 5: Kolmogorov–Smirnov Test of Normality (N = 200).

3.5 Reliability

Internal consistency results are presented in Table 6. All five constructs exceeded the .70 threshold. Cronbach's alpha was .768 for OR, .747 for LRR, .706 for SE, .762 for TI, and .763 for FIHP.

Construct	No. of items	M	SD	Cronbach's α
Operational Readiness (OR)	4	3.04	0.62	.768
Legal and Regulatory Requirements (LRR)	4	3.33	0.85	.747
Stakeholder Engagement (SE)	4	3.89	0.64	.706
Technological Infrastructure (TI)	4	4.14	0.81	.762
Feasibility of Implementing a Health Platform (FIHP)	5	3.64	0.68	.763

Table 6: Internal Consistency of Constructs (N = 200).

3.6 Factor Analysis

The KMO measure of sampling adequacy was .854, and Bartlett's test of sphericity was significant, $\chi^2(210) = 1532.884$, $p < .001$ (Table 7).

Measure	Value
Kaiser-Meyer-Olkin measure of sampling adequacy	.854
Bartlett's test of sphericity: approx. χ^2	1532.884
df	210
Sig.	< .001

Table 7: KMO and Bartlett's Test.

Principal component analysis with varimax rotation produced a five-component solution. The five retained components had initial eigenvalues of 6.615, 1.976, 1.485, 1.149, and 1.046, together explaining 58.432% of the total variance. After rotation, the components accounted for 15.029%, 12.500%, 12.110%, 9.511%, and 9.283% of variance, respectively.

Rotated factor loadings, CR, and AVE values are presented in Table 8. CR values exceeded .70 for all constructs: OR (CR = .767), LRR (CR = .791), SE (CR = .722), TI (CR = .757), and FIHP (CR = .720). AVE values were below the .50 benchmark for all of the five constructs: LRR (AVE = .490), OR (AVE = .456), TI (AVE = .439), SE (AVE = .407), and FIHP (AVE = .341). The lowest individual loadings were observed for SE1 (.403) and FIHP3 (.480).

Construct	Item	Loading	CR	AVE
Operational Readiness (OR)	OR1	.785	.767	.456
	OR2	.614		
	OR3	.556		
	OR4	.721		
Legal and Regulatory Requirements (LRR)	LRR1	.626	.791	.490
	LRR2	.794		
	LRR3	.629		
	LRR4	.734		
Stakeholder Engagement (SE)	SE1	.403	.722	.407
	SE2	.698		
	SE3	.579		
	SE4	.803		
Technological Infrastructure (TI)	TI1	.700	.757	.439
	TI2	.568		
	TI3	.679		
	TI4	.695		
Feasibility of Implementing a Health Platform (FIHP)	FIHP1	.594	.720	.341
	FIHP2	.600		
	FIHP3	.480		
	FIHP4	.617		
	FIHP5	.618		

Table 8: Rotated Factor Loadings, Composite Reliability, and Average Variance Extracted.

3.7 Correlation Analysis

Pearson correlations among the five constructs are presented in Table 9. All correlations were positive and statistically significant at the .01 level. FIHP correlated most strongly with TI ($r = .649$, $p < .001$), followed by SE ($r = .585$, $p < .001$), OR ($r = .550$, $p < .001$), and LRR ($r = .462$, $p < .001$). Among the independent constructs, the strongest association was between SE and TI ($r = .606$, $p < .001$), followed by LRR with TI ($r = .483$, $p < .001$) and LRR with OR ($r = .460$, $p < .001$).

The weakest association was between OR and TI ($r = .324$, $p < .001$).

Construct	FIHP	OR	LRR	SE	TI
FIHP	1				
OR	.550**	1			
LRR	.462**	.460**	1		
SE	.585**	.368**	.420**	1	
TI	.649**	.324**	.483**	.606**	1

Table 9: Pearson Correlations Among Constructs (N = 200).

Note. ** Correlation is significant at the .01 level (two-tailed).

3.8 Regression Analysis

Results of the multiple linear regression are presented in Table 10. The model produced a multiple correlation of $R = .760$, with $R^2 = .577$ and adjusted $R^2 = .569$, and a standard error of the estimate of 0.444. The overall model was significant, $F(4, 195) = 66.554$, $p < .001$, with a regression sum of squares of 52.464 and a residual sum of squares of 38.429 out of a total of 90.893.

Three of the four predictors were significant. TI recorded the largest standardized coefficient ($\beta = .402$, $t = 6.513$, $p < .001$), followed by OR ($\beta = .330$, $t = 6.150$, $p < .001$) and SE ($\beta = .207$, $t = 3.426$, $p = .001$). LRR was not a significant predictor ($\beta = .029$, $t = 0.504$, $p = .614$). The constant was not significant ($B = 0.240$, $t = 1.100$, $p = .273$).

Tolerance values ranged from .57 to .75 and VIF values from 1.33 to 1.76, well below the threshold of 5, indicating no problematic multicollinearity among the predictors (Table 10). The 95% confidence intervals for the coefficients of TI, OR, and SE did not include zero, whereas the interval for LRR did (Table 10).

Predictor	B	SE B	β	t	p	95% CI for B	Tolerance	VIF
(Constant)	0.240	0.218		1.100	.273	[−0.190, 0.670]		
Operational Readiness (OR)	0.359	0.058	.330	6.150	< .001	[0.245, 0.473]	.75	1.33
Legal and Regulatory Requirements (LRR)	0.023	0.046	.029	0.504	.614	[−0.068, 0.114]	.66	1.52
Stakeholder Engagement (SE)	0.218	0.064	.207	3.426	.001	[0.092, 0.344]	.59	1.69
Technological Infrastructure (TI)	0.336	0.052	.402	6.513	< .001	[0.233, 0.439]	.57	1.76

Table 10: Multiple Linear Regression Predicting Feasibility of Implementing a Health Platform (N = 200).

Note. B = unstandardized coefficient; SE B = standard error of B; β = standardized coefficient; CI = confidence interval; VIF = variance inflation factor. Tolerance and VIF were derived from the correlations among the predictors (Table 9).

4. Discussion

4.1 Overview of Findings

This survey assessed readiness for the 10P-Health platform among adult residents of Bavaria and examined the factors associated with its perceived feasibility. Respondents were predominantly young highly educated, reported broad prior exposure to digital health, and perceived feasibility was moderate overall. The regression model explained a substantial share of the variance in perceived feasibility, with technological infrastructure, operational readiness, and stakeholder engagement emerging as significant predictors and legal and regulatory requirements not reaching significance. The pattern of responses indicates a divergence between confidence in technological and personal capacity, and confidence in institutional capacity.

4.2 Operational Readiness and Institutional Capacity

Operational readiness received the lowest overall assessment among the constructs, with concerns particularly evident regarding system resources, including funding, trained staff, and technical infrastructure. Perceived training and comfort of healthcare professionals with digital tools were also relatively low, while provider preparedness showed a similarly limited assessment. Despite these reservations, operational readiness emerged as the second strongest predictor of perceived feasibility, indicating that respondents linked the feasibility of personalized digital health implementation closely to institutional capacity even while perceiving that capacity as limited.

These perceptions can be read against the broader context described in the literature. The German digital health market has continued to expand in recent years, providing a favorable macroeconomic backdrop. However, regional infrastructure gaps, including incomplete 5G coverage in rural areas, may constrain scalability [20], while regulatory complexity in a multi-stakeholder environment may further limit the scalability of digital health solutions [21]. Concerns regarding staff competence are consistent with arguments that digital health adoption depends on upskilling doctors, nurses, data scientists, and IT specialists [22], embedding AI literacy into medical education [23], and ensuring the availability of cybersecurity specialists, AI engineers, and compliance officers [24]. The GDPR requirement to appoint data protection officers further underlines the need for specialized governance expertise [25,26].

Notably, respondents demonstrated greater willingness to pay a reasonable amount for personalized digital health services than the level of confidence expressed regarding system resources and staff competence. This suggests that respondents' openness to adoption may not represent the principal constraint identified by respondents; rather, institutional capacity and workforce preparedness appear to represent more significant barriers.

4.3 Legal and Regulatory Requirements

Legal and regulatory requirements received a moderate overall assessment. Respondents expressed broadly similar levels of trust in the ability of certified platforms to protect data privacy and security, confidence in the protection afforded by existing laws such as the GDPR, and the perceived ease of giving or withdrawing consent. In contrast, clarity regarding how health data are collected, used, and shared received the weakest assessment within this construct. This pattern suggests that respondents place greater confidence in the existence of formal legal protections than in the transparency of everyday data practices.

The literature offers a consistent account of this gap. The GDPR establishes clear requirements concerning consent, data minimization, and pseudonymization or anonymization [27,28], while the BDSG reinforces patient rights relating to rectification and erasure [29]. The Patient Data Protection Act allows patients to make EHR available for research where they provide explicit consent [30]. At the same time, meeting these formal requirements does not by itself guarantee that data practices are

transparent to patients, as data protection impact assessments intended to mitigate such risks are not uniformly standardized at the clinical level [31].

The finding suggests that respondents view regulation primarily as a necessary background condition. Legal safeguards nevertheless remain important to adoption, since AI-driven healthcare must meet requirements relating to patient rights, ethics, and data protection, while questions concerning liability for AI-assisted decisions remain unresolved under German law [32]. Depending on their intended use, healthcare AI systems may also be subject to additional regulatory requirements concerning explainability, bias mitigation, and ongoing auditing.

4.4 Stakeholder Engagement and Trust

Stakeholder engagement received one of the strongest overall assessments and included the highest-rated item in the survey. Respondents strongly endorsed the principle that digital health services should be accessible and inclusive regardless of income, disability, or language, and supported the involvement of patients and citizens in the development of new services. Trust in digital health systems and AI-generated recommendations was more moderate and appeared conditional on appropriate supervision by medical professionals. At the same time, respondents expressed comparatively less confidence that existing digital health tools are adequately designed around patients' needs and incorporate patient feedback. This indicates a perceived gap between the participatory principles that respondents endorse and the patient-centeredness of currently available tools.

Stakeholder engagement was also positively associated with perceived feasibility and showed a strong relationship with technological infrastructure. These findings align with accounts describing trust as a prerequisite for digital health adoption rather than merely an influencing factor, with trust anchored in confidentiality, physician endorsement, and confidence in the healthcare system. Policy frameworks are relevant in this context: the Digital Healthcare Act has institutionalized reimbursement for digital health applications [33], while the Bavarian State Ministry of Health and Care acts as both regulator and strategic investor in digital health innovation [34]. Preparedness among future clinicians is also relevant: a survey of first-year medical students at two Munich universities found that two-thirds did not feel well informed about AI in medicine, and only just over half considered AI to have useful medical applications, most often in drug research and development rather than in clinical use [35]. Together with the conditional nature of respondents' trust in AI, these findings suggest that physician oversight and participatory design are important conditions for public acceptance of digital health technologies.

4.5 Technological Infrastructure

Technological infrastructure received the strongest overall assessment and emerged as the most important predictor of perceived feasibility. Respondents expressed confidence in access to internet and mobile networks, strongly endorsed the seamless sharing of health records among treating clinicians, and supported interoperability between digital systems and applications. Openness to AI and analytics for prediction or prevention was also favorable, although responses were more varied than those concerning connectivity and interoperability. This suggests that respondents may be more consistently comfortable with the foundational infrastructure required for digital health than with the application of AI-based tools.

Two features of these findings warrant attention. First, several of the most highly rated infrastructure items are expressed as expectations or requirements rather than direct descriptions of current provision. Consequently, positive assessments may reflect what respondents consider necessary for effective digital health implementation as much as what they currently experience. Second, respondents' confidence in their own connectivity contrasts with reported connectivity gaps in rural areas of Bavaria [20,36] and with observations that rural settings may face slower systems and more limited AI acceptance. Interoperability nevertheless remains a documented constraint, international standards such as HL7, DICOM, and FHIR are considered central to secure data sharing between providers and AI systems,

yet Germany's federated healthcare structure complicates integration [37], while fragmentation across federal states can hinder interoperability and data exchange [38]. Investment costs may also limit adoption, particularly among small and medium-sized healthcare organizations.

5. Limitations

Several limitations should be considered when interpreting these findings. First, the sample size was small, which reduces statistical power and the precision of the estimates. Second, the sample was geographically concentrated, with 79.5% of respondents located in Lower Bavaria and Upper Bavaria; perceptions in Franconia, Swabia, and the Upper Palatinate are correspondingly underrepresented, and the findings cannot be generalized to all of Bavaria. Third, the sample was predominantly young and highly educated: half of the respondents were aged 25 to 34 years, and 74.0% held at least a Bachelor's degree. Older adults and respondents with lower formal education, groups whose digital access and attitudes may differ, were underrepresented, which is particularly relevant for a platform intended to be inclusive.

Fourth, all data were self-reported and are therefore subject to social desirability and self-selection bias. Fifth, the cross-sectional design captures perceptions at a single point in time and does not permit causal inference; the regression results describe associations, not effects. Sixth, all item distributions deviated significantly from normality, as is common with Likert-type data, and results based on parametric procedures should be interpreted with corresponding caution. Seventh, the constructs were measured with newly developed items, and their AVE values fell below .50; although composite reliability was adequate, the measurement model should be confirmed with confirmatory factor analysis in a larger, independent sample. Finally, the survey measured perceived feasibility among residents rather than the operational or legal feasibility of implementation itself, and the findings should be read as evidence of respondents' readiness and expectation rather than of institutional capacity.

6. Conclusion

The 10P-Health framework represents a comprehensive, platform-based model of personalized care, extending earlier P-medicine paradigms through ten principles and reflecting the convergence of personalized medicine with digital health, big data, and AI. Realizing such a model in practice depends not only on technical capability but also on public readiness and the perceived feasibility of implementation.

This cross-sectional survey of adult residents of Bavaria found moderate readiness for the 10P-Health platform among respondents. Respondents were broadly experienced with digital health tools, endorsed inclusive access, interoperability, and patient consultation, and expressed conditional trust in AI-supported care under medical supervision. Perceived feasibility was significantly predicted by technological infrastructure, operational readiness, and stakeholder engagement, while legal and regulatory requirements function as a background condition rather than a direct driver of perceived feasibility. The clearest reservations concerned institutional capacity, as system resources and provider preparedness received the lowest ratings in the survey. Within the limits of a regionally concentrated, predominantly young and educated sample, these findings indicate that respondents' attitudes do not present the principal obstacle to a personalized digital health platform in Bavaria, and they identify institutional readiness, transparent data practices, and interoperable infrastructure as the areas in which respondents perceived the greatest need for development. Longitudinal and more representative studies would be required to confirm these associations and to track readiness as implementation proceeds.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Continuous, Person-Centered Digital Precision Health and Wellness: A Structured Narrative Review Informing 10P-Health

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ABSTRACT

Background: Continuous, person-centered digital precision health and wellness aims to complement episodic, illness-triggered care with longitudinal multimodal data, analytical support, and accountable responses. 10P-Health (10PH) is the authors' integrated formulation, organized around ten interdependent principles.

Objective: To examine literature and initiatives relevant to 10PH, identify capabilities, implementation conditions, limitations, and gaps in evidence on connections across principles and measurement-to-response pathways.

Methods: A non-exhaustive structured narrative review used PubMed, IEEE Xplore, Google Scholar, citation searching, and targeted official sources. English-language material from 2013 to 2026 was considered, with earlier seminal work retained for conceptual lineage. Heterogeneous conceptual, empirical, technical, policy, program, and product sources were organized by conceptual development, enabling data and technology, initiatives and products, implementation conditions, and evidence maturity. Source-reported findings were distinguished from author interpretation.

Results: The literature describes population-scale genomic and phenotypic resources, longitudinal multimodal programs, remote-monitoring workflows, digital-twin applications, interoperability approaches, and person- and organization-facing artificial intelligence products. It also identifies governance, privacy, safety, professional workflow, participation, equity, access, and economic evaluation as implementation requirements. The sources generally addressed individual capabilities or bounded workflows; evidence on how these connect across settings into end-to-end measurement-to-response pathways remains fragmented. No reviewed source evaluated 10PH as a complete integrated intervention.

Conclusion: Existing evidence identifies capabilities and implementation conditions relevant to 10PH but does not establish the integrated framework's feasibility, effectiveness, safety, equity, or cost-effectiveness. Future research should prospectively and independently evaluate defined use cases to test how data, validated interpretation, pertinent responses, accountable workflows, and meaningful person participation connect.

KEYWORDS

Longitudinal health data, artificial intelligence, interoperability, data governance, remote monitoring

List of abbreviations

Abbreviation	Meaning
10PH	10P-Health
AI	artificial intelligence
EHR	electronic health record
FHIR	Fast Healthcare Interoperability Resources
P4	predictive, preventive, personalized, and participatory medicine

1. Introduction

1.1 From P4 Medicine to continuous digital precision health

P4 Medicine articulated a shift from reactive disease treatment toward predictive, preventive, personalized, and participatory care [1, 2]. Hood [3] linked this vision to systems medicine, omics, and network models; Flores et al. [4] emphasized systems biology, digital technologies, and individual participation. Later formulations broadened this foundation in different contexts: P5 added a psycho-cognitive dimension [5], P6 a public dimension [6], and P9 pervasive, precise, privacy-preserving, protective, and reasonably priced attributes within networked healthcare [7]. These formulations are related extensions, not a standardized sequence or hierarchy.

Research on longitudinal multi-omics, electronic health record (EHR) integration, digital twins, and remote monitoring illustrates capabilities for risk estimation, individualized interpretation, and follow-up in defined settings [8–11]. Responsible implementation also depends on interoperability, governance, professional workflows, participation, and equity [12–16]. However, evidence that individual technologies, programs, or implementation conditions can support particular functions does not establish that they work together as a coherent health pathway. The extent to which longitudinal data, validated interpretation, pertinent preventive or proactive responses, accountable workflows, and person participation are connected and evaluated across settings remains insufficiently established.

Building on the earlier P4-P9 concepts, Georgi Chaltikyan started using the term 10P-Health in his lectures and public talks in 2019 (Chaltikyan, personal communication, Nov 14, 2019). He subsequently described 10P-Health as the novel "21st-century health and wellness paradigm" [17]. In this review, we use 10P-Health (10PH) as an integrated formulation of continuous digital precision health and wellness that extends attention beyond episodic patient care to people – including those who are currently healthy – across the life course. Its ten interdependent P-principles are Predictive, Preventive, Personalized/Precision, Proactive, Participatory, Pertinent, Pervasive, Permanent, Privacy-Preserving, and Platform-Based. The framework envisages governed use of longitudinal, multimodal information from clinical records, omics, behavior, lifestyle, environment, wearables, home sensors, and other connected sources to support timely interpretation and action. The framework's potential value lies not simply in accumulating data or technologies, but in connecting them to pertinent, validated interpretation and feasible responses while preserving accountability, participation, and privacy. The principles are therefore interdependent: predictive and personalized/precision insights need to inform relevant preventive or proactive action; pervasive and permanent engagement depends on suitable platform infrastructure; and participation

requires privacy protection and accountable governance. Evidence for these elements in isolation does not establish health benefit from an integrated model. As a conceptual vision, it requires use-case-specific validation, professional oversight, safety controls, consent, privacy protection, proportionate data access, equity safeguards, and attention to overmedicalization.

1.2 Aim and scope of the review

This structured narrative review examines international literature, projects, programs, infrastructures, implementations, and selected products relevant to the emergence of continuous, person-centered, digitally enabled precision health and wellness. It synthesizes their purposes, intended users, data sources, functions, implementation status, reported findings, and limitations while considering interoperability, governance, privacy, safety, professional responsibility, participation, equity, access, and evidence maturity.

The review asks which evidence and initiatives inform this vision, what capabilities, implementation conditions, and limitations they reveal, and whether the literature examines how these components connect across principles into integrated measurement-to-response pathways – or leaves these connections insufficiently evaluated. It maps the evidence landscape without testing framework superiority or inferring integrated-model feasibility, effectiveness, safety, equity, or cost-effectiveness from component evidence.

2. Methodology

2.1 Review design and question

This structured narrative review examined literature, projects, programs, infrastructures, implementations, and selected products relevant to continuous, person-centered, digitally enabled precision health and wellness. It asked which sources and initiatives inform this landscape and what capabilities, implementation conditions, limitations, and gaps they reveal for 10P-Health (10PH). The review accommodated heterogeneous conceptual, empirical, technical, policy, program, and product sources. It was interpretive and non-exhaustive; it was not intended to estimate pooled effects, test framework superiority, or establish the feasibility, effectiveness, safety, equity, or cost-effectiveness of integrated 10PH.

2.2 Information sources and searches

PubMed, IEEE Xplore, and Google Scholar were searched. PubMed was searched in April 2026, and IEEE Xplore and Google Scholar were searched in May 2026. Targeted citation searching and official-source updates were completed on 31 July 2026.

Searches targeted English-language sources published from 2013 to 2026; earlier seminal publications were eligible when needed to trace P4 Medicine and related conceptual lineage. Database searching was supplemented by citation searching and targeted examination of official sources for public agencies, research programs, infrastructures, policy or regulatory guidance, and selected products. Official product information was checked against the current vendor pages on 31 July 2026.

Searches were organized into four themes rather than requiring every record to contain all 10PH terms: (1) P4 and related formulations, precision health, personalized healthcare, and Digital Precision Health; (2) longitudinal and multimodal data, omics, EHRs, wearables, remote monitoring, artificial intelligence (AI), digital twins, interoperability, and platform infrastructures; (3) projects, programs, population-scale resources, implementations, and person- or professional-facing products; and (4) governance, privacy, safety, consent, workflow, participation, equity, access, adoption, sustainability, and economic evaluation. The final executed search strings are reported in Appendix 1.

2.3 Eligibility and source selection

Sources were considered when they addressed at least one of four areas: conceptual development of continuous precision health; a digital, clinical, data, or analytical capability relevant to longitudinal, preventive, proactive, personalized, or participatory support; an implementation condition such as interoperability, governance, privacy, safety, workflow, equity, access, adoption, financing, or sustainability; or a named initiative combining materially relevant functions. Eligible source types included empirical studies, reviews, conceptual papers, technical studies with an explicit health or implementation relationship, economic-methods papers, authoritative guidance, official program or infrastructure reports, and official product information. Official sources were used to describe current functions; independent evaluations were prioritized for performance or outcome claims.

Duplicate records were not treated as separate sources. Non-English publications, purely technical performance studies without a health or implementation relationship, clinical studies without a relevant digital or precision-health dimension, and unverifiable promotional material were excluded. Opinion and commentary sources were retained only for identified conceptual contributions or to define an evidence gap. Candidate records were assessed from titles and abstracts or summaries, followed by full texts or documents where required. Supplementary sources followed the same eligibility logic.

Source selection occurred within the framework-development author team, and no reviewer outside that team adjudicated inclusion. A total of 3,986 records were identified through database searches (Google Scholar, PubMed, and IEEE Xplore). After removal of 8 duplicate records, 3,978 records were screened, of which 3,906 were excluded because they lacked direct relevance, were not aligned with the review aim, or showed conceptual overlap. Of 72 reports sought for retrieval, 4 could not be retrieved, and 68 were assessed for eligibility; 22 were excluded because of a non-health/wellness or predominantly technical focus, and 17 because they provided insufficient implementation detail, resulting in 29 studies included from database searching. An additional 8 reports were identified through websites and organizations, of which 3 were excluded as not aligned with the review aim, resulting in 5 further reports. A PRISMA-style-adapted flow diagram summarizing the identification, screening, and inclusion process is provided below (Figure 1).

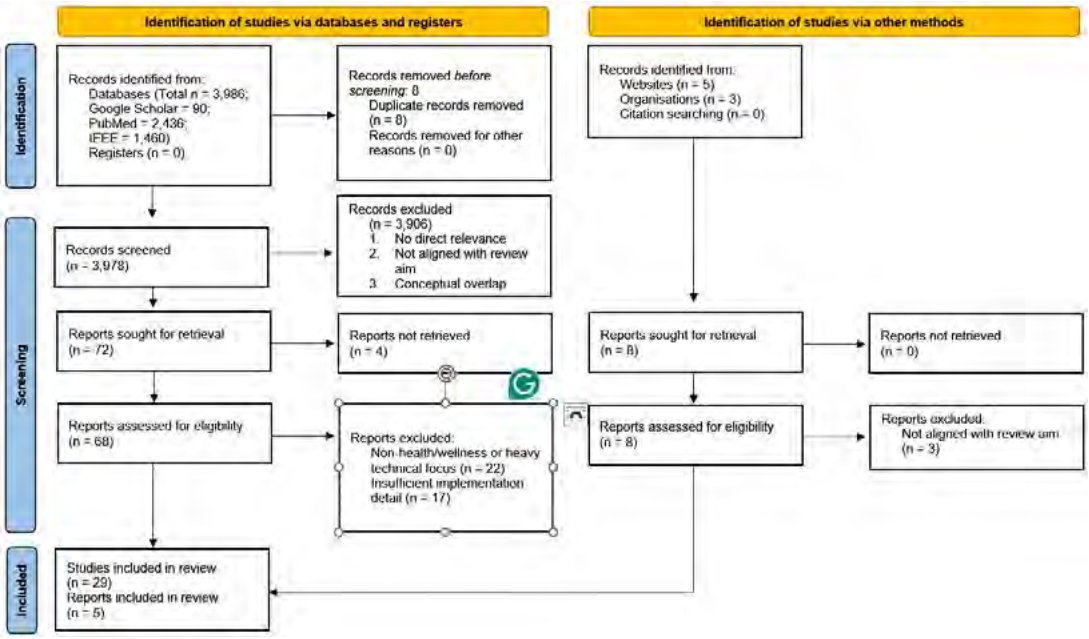


Figure 1: Adapted PRISMA 2020 flow diagram illustrating the study identification and selection process, including records from

databases and other sources, Page, McKenzie, et al., 2021 [18].

2.4 Information organization and narrative synthesis

Information from each retained source or initiative was organized by source type, purpose, intended users or population, setting, data sources, functions, implementation status, methods or design, reported findings, and limitations. Sources were differentiated as conceptual literature; empirical studies and reviews; initiative descriptions; policy or guidance; or official product information.

The narrative synthesis grouped material across conceptual lineage; enabling data and technology; programs, infrastructures, and products; implementation conditions; and evidence maturity and gaps. For presentation, the seven evidence groups summarized in Table 1 were mapped interpretively to the ten 10PH principles and the four thematic Results domains (Sections 3.2–3.5). These mappings were non-exclusive and author-derived: individual sources could inform multiple principles or domains, and the mappings represent the review team's interpretation of relevance rather than classifications used by the original sources or direct validation of the 10PH framework. The narrative synthesis distinguished direct evidence concerning 10PH or a complete integrated model, indirect evidence concerning components or implementation domains, official descriptions, and author-derived interpretation. Heterogeneous source types were not treated as equivalent, and product descriptions were not treated as safety or effectiveness evidence. No meta-analysis or formal risk-of-bias or quality scoring was undertaken because the review question and source types were heterogeneous and the review did not estimate intervention effects.

3. Results

3.1 Evidence landscape and evidence maturity

The reviewed material represented a heterogeneous evidence landscape rather than a single intervention literature. It included population-scale research resources; longitudinal multimodal cohort and wellness studies; reviews of digital twins, interoperability, professional adoption, public attitudes, and economic evaluation; an implementation-effectiveness study of remote symptom monitoring; equity and patient-involvement analyses; authoritative governance guidance; and official descriptions of selected current products. Consistent with the non-exhaustive narrative design, the findings are organized by evidence group and initiative type without numerical aggregation or ranking across unlike source types.

No reviewed source evaluated 10P-Health (10PH) as a complete ten-principle intervention or used the full formulation as an empirical evaluation framework; direct evidence for the integrated model was therefore absent. Table 1 makes explicit the author-derived relationships between the seven evidence groups and the 10PH principles they most directly inform. The four thematic Results domains organize these groups as follows: Section 3.2 covers population-scale research resources and longitudinal multimodal programs; Section 3.3 covers digital twins and monitoring workflows and person- and organization-facing AI products; Section 3.4 covers interoperability and governance and adoption, participation, and equity; and Section 3.5 covers economic evaluation and cross-domain synthesis. These mappings are non-exclusive and indicate conceptual relevance, not classifications used by the original sources or evidence that the corresponding principles have been validated individually or together. The central gap is therefore not simply the absence of individual capabilities, but the limited evidence on whether these capabilities connect into coherent measurement-to-response pathways linking validated interpretation to appropriate action under accountable governance and with meaningful person participation. Empirical studies and program descriptions provide indirect evidence about components or bounded workflows; reviews and guidance identify implementation conditions; and vendor pages describe stated functions and availability. The cross-domain synthesis in Section 3.5 is an author-derived interpretation rather than an empirically tested model.

Evidence group/ 10PH relevance	Representative sources	Reported contribution	Inferential boundary
Population-scale research resources/ Predictive; Personalized/Precision	All of Us Research Program Genomics Investigators (2024) [19]; Bycroft et al. (2018) [20]; Kurki et al. (2023) [21]	Large-scale genomic, phenotypic, longitudinal, and governed research resources support discovery and model development.	Research resources do not establish continuous care, clinical utility, preventive action, or equitable benefit.
Longitudinal multimodal programs/ Predictive; Personalized/Precision; Pertinent; Permanent*	Hou et al. (2020) [22]; Price et al. (2017) [23]; Schüssler-Fiorenza Rose et al. (2019) [10]; Tong et al. (2024) [11]	Repeated clinical, molecular, behavioral, imaging, and activity data can be combined with interpretation or coaching.	Mostly descriptive or non-randomized evidence; comparative effectiveness, long-term safety, access, and value remain unestablished.
Digital twins and monitoring workflows/ Predictive; Preventive*; Personalized/Precision; Proactive; Pertinent; Participatory**	Armeni et al. (2022) [8]; Kaplan et al. (2023) [24]; Riahi et al. (2025) [25]; Rocque et al. (2025) [9]	Reviews describe longitudinal models; one oncology study reports a defined remote symptom-monitoring workflow and outcome associations; commentary identifies monitoring harms that require empirical study.	Definitions and maturity vary; setting-specific, non-randomized findings do not validate an integrated framework, and the frequency of possible harms is not established.
Person- and organization-facing AI products/ Personalized/Precision; Proactive; Platform-Based	Anthropic (2026) [26]; OpenAI (2026a, 2026b) [27, 28]	Official sources describe optional health-data connections, information support, and healthcare-organization offerings.	Vendor descriptions establish stated functions and status, not independent evidence of accuracy, safety, effectiveness, or equity.
Interoperability and governance/ Privacy-Preserving; Platform-Based	Heryawan et al. (2025) [29]; Lehne et al. (2019) [14]; Torab-Miandoab et al. (2023) [30]; World Health Organization (2021) [16]	Layered exchange requirements and ethics, accountability, transparency, inclusion, and human oversight are recurrent conditions.	No single standard or governance configuration is shown to fit every use case or validate 10PH.
Adoption, participation, and equity/ Participatory; Pervasive; Privacy-Preserving	Bertelsen et al. (2024) [12]; Borges do Nascimento et al. (2023) [13]; Chen et al. (2025) [31]; Rao et al. (2024) [15]	Workflow, workforce, attitudes, meaningful influence, access, and distributional effects require explicit attention.	The sources do not show that a service described as 10PH will be adopted, participatory, accessible, trusted, or equitable.
Economic evaluation/ Cross-cutting relevance to Pervasive (access and affordability) and Platform-Based (implementation and maintenance costs)	Gavan et al. (2018) [32]; Gentili et al. (2022) [33]; Love-Koh et al. (2018) [34]; O'Mahony et al. (2015) [35]	Comparator, perspective, uncertainty, implementation cost, and time horizon shape value assessment.	No direct evidence establishes 10PH affordability, budget impact, or cost-effectiveness.

Table 1: Evidence groups relevant to 10PH and their inferential boundaries.

*Note. Source types are heterogeneous. The 10PH mappings are author-derived, non-exclusive indicators of conceptual relevance, not classifications used by the cited sources and not evidence that any individual principle or the integrated framework has been validated. **For remote symptom monitoring, Participatory refers to contributing patient-reported data and does not necessarily imply influence over decisions. *The reviewed sources do not establish preventive health benefit or permanent support across the life course; the links between monitoring and Preventive, and between longitudinal programs and Permanent, are therefore conceptual rather than demonstrated. Product descriptions establish stated functions and release status only; economic sources inform evaluation questions but do not establish 10PH affordability or cost-effectiveness.*

Geographic context varied across the reviewed material and depended on the type of evidence. The principal empirical and infrastructure examples included the United Kingdom (UK Biobank), the United States (All of Us and US-based precision-health and remote-monitoring studies), Finland (FinnGen), and Indonesia (a national FHIR-based interoperability implementation). These examples represent different research and implementation contexts, including population-scale data linkage, longitudinal research cohorts, clinical monitoring, and national interoperability initiatives. Other sources comprised multi-country reviews, global guidance, or vendor descriptions rather than studies conducted within a single national healthcare system.

3.2 Population-scale and longitudinal precision-health infrastructures

Population-scale initiatives showed that genomic, phenotypic, and longitudinal information can be assembled within reusable research infrastructures. UK Biobank enrolled approximately 500,000 participants and combined genomic data with deep phenotyping and linked health information [20]. The All of Us Research Program reported 245,388 clinical-grade genome sequences alongside longitudinal EHR and other phenotypic data; 77% of participants in that analysis were from communities historically underrepresented in biomedical research and 46% were from underrepresented racial and ethnic minority groups [19]. FinnGen linked biobank-derived genotype data with national health-register data through a public-private research partnership [21]. These resources support discovery, model development, linkage, and governed reuse. They are research infrastructures, not evaluations of continuous individual-level care pathways, and they do not establish that data assembly produces timely preventive action or improved outcomes.

Smaller longitudinal programs demonstrated operational combinations of repeated measurements and individualized interpretation. Schüssler-Fiorenza Rose et al. [10] related repeated molecular, clinical, physiological, and behavioral measurements to changing health states. A Human Longevity, Inc. study combined whole-genome sequencing, metabolomics, imaging, laboratory testing, and multidisciplinary review in 1,190 adults [22]. The Pioneer 100 Wellness Project combined genome sequencing, repeated clinical and multi-omic measurements, activity tracking, and health coaching in 108 participants over nine months [23]. A review of multi-omics and EHR integration described analytical methods that could support precision-oriented modelling [11]. These sources show that multimodal data and interpretive functions can be assembled, but their observational, descriptive, or non-randomized designs do not establish comparative effectiveness, long-term safety, accessibility, or cost-effectiveness.

Taken together, these initiatives provide indirect evidence for the informational and longitudinal capabilities envisaged in 10PH. However, these do not demonstrate the full measurement-to-response pathway – from representative data and validated inference to pertinent action, accountable professional workflows, person participation, and sustained preventive benefit – or test how these elements operate together. The association of these infrastructures with particular 10PH dimensions is therefore an author-derived mapping, not a classification used by the source programs; integration of data modalities within a research resource should not be conflated with integration across the ten principles in practice.

3.3 Continuous monitoring, predictive modelling, and person-facing AI

Digital-twin reviews described models that combine person, device, or operational data over time for simulation or decision support, while also reporting heterogeneous definitions, variable validation, and early implementation maturity [8, 25]. These reviews support the relevance of longitudinal modelling but do not establish clinical utility for a common digital-twin intervention. Likewise, analytical capability alone does not show that an estimate is externally valid, understandable, actionable, or linked to a safe response pathway.

Remote electronic patient-reported outcome monitoring offered a more defined measurement-to-response workflow. In a non-randomized hybrid type 2 implementation-effectiveness study of 5,949 people receiving cancer care, 1,392 participants using remote symptom monitoring were compared with

4,557 historical controls. Adjusted analyses associated monitoring with 19% lower hospitalization risk at three months and 13% lower risk at six months; emergency-department and intensive-care use did not differ significantly [9]. The historical comparator, oncology setting, and bounded follow-up limit causal and cross-setting inference. The study evaluates a specific clinical workflow, not 10PH, and any mapping to participatory, pervasive, pertinent, or proactive dimensions is author-derived.

The potential adverse consequences of continuous consumer monitoring remain less mature as an evidence domain. Kaplan et al. [24] called for empirical investigation of possible harms from consumer wearables, including psychological, behavioral, and healthcare-use consequences. This commentary defines a research need; it does not establish the incidence or severity of those outcomes or demonstrate harms caused by 10PH.

Official vendor sources described a newer category of person-facing AI products. As of 31 July 2026, OpenAI reported that Health in ChatGPT was rolling out on web and iOS to logged-in users aged 18 years or older in the United States. The vendor described optional connections to Apple Health and supported medical records for functions such as reviewing results, summarizing changes, identifying trends, and preparing for appointments [28]. Anthropic described opt-in health-record, laboratory, and fitness-data connections for Claude Pro and Max users in the United States, including beta integrations with HealthEx, Function, Apple Health, and Android Health Connect [26]. Both vendors also described organization-facing healthcare offerings [26, 27]. These are official product descriptions, not independent evaluations. Within the reviewed material, they establish stated functions and release status but not diagnostic accuracy, clinical effectiveness, safety, continuity, equitable access, or performance as integrated 10PH implementations. Across these examples, the degree and type of integration differ: digital-twin reviews address longitudinal modelling, remote symptom monitoring evaluates a defined clinical workflow, and vendor sources describe stated product functions. The reviewed material does not establish whether these capabilities can be connected into a validated end-to-end pathway linking reliable interpretation to pertinent responses, assigned responsibility, sustained follow-up, and meaningful person participation.

3.4 Interoperability, governance, participation, and equity

The implementation literature treated interoperability as layered rather than solely technical. Lehne et al. [14] distinguished technical, syntactic, semantic, and organizational interoperability. A review of heterogeneous health information systems identified recurring standards, terminology, architecture, policy, and organizational requirements [30], while a setting-specific analysis of Fast Healthcare Interoperability Resources (FHIR) implementation in Indonesia documented practical design and developer challenges [29]. These sources support the need to preserve meaning and responsibility across systems; they do not show that one standard or architecture is sufficient for all use cases.

Governance evidence extended beyond exchange. World Health Organization guidance identified ethics, human rights, transparency, accountability, inclusion, safety, and human oversight as central to AI for health [16]. Applied to longitudinal and multimodal systems, these are implementation conditions rather than proof of responsible operation. The relevance of controlled access, data stewardship, contestability, and purpose limitation to the Privacy-Preserving and Platform-Based dimensions is an author-derived interpretation. The reviewed guidance did not validate a specific governance configuration for 10PH.

Professional adoption and organizational fit were recurrent workflow constraints. An umbrella review of health professionals' use of digital technologies identified infrastructure and technical problems, workload, psychological barriers, training, perceived usefulness, and organizational support as recurring influences on adoption [13]. The findings show why technical availability cannot be equated with routine use. They do not establish which combination of implementation strategies would be sufficient for a service described as 10PH.

Participation and equity also required distinctions between data contribution, influence, access, and benefit. Bertelsen et al. [12] identified 53 patient-engagement or patient-experience initiatives and resources in regulatory review and health technology assessment; 11% demonstrated integration of both domains. A systematic review of 562 studies on public and patient attitudes toward health-monitoring technologies reported generally positive attitudes alongside geographic and representation gaps and concerns about privacy, affordability, technical errors, burden, and over-reliance [31]. Rao et al. [15] showed how equity-focused implementation frameworks could be applied to population genetic screening. The diversity profile reported by All of Us broadened representation in its genomic resource, but demographic inclusion itself did not demonstrate influence over decisions, equitable access to resulting services, or equitable health benefit [19]. The evidence therefore supports explicit examination of who participates, how influence is exercised, who can use a service, and how benefits and burdens are distributed; it does not show that digitally enabled participation is inherently representative or equitable. Taken together, these findings suggest that interoperability, governance, workforce and organizational readiness, meaningful participation, and equity should be examined as interdependent conditions for implementation rather than as separate requirements assessed in isolation; the reviewed sources do not establish how these conditions should be coordinated within an integrated 10PH pathway.

3.5 Economic evidence and overall synthesis

Economic sources informed evaluation questions rather than a conclusion about 10PH value. Gavan et al. [32] framed the economic case for precision medicine around payer-relevant value and uncertainty. Love-Koh et al. [34] described challenges that precision medicine can create for health technology assessment, and a review found heterogeneous methods and cost-effectiveness findings across digital health interventions, limiting comparison and transferability [33]. O'Mahony et al. [35] emphasized the need for analytic time horizons long enough to capture relevant costs and outcomes. None of these sources evaluated 10PH. The Human Longevity and Pioneer 100 studies likewise did not compare costs and outcomes with usual care or establish affordability, budget impact, or distributional access [22, 23]. Across the evidence groups, the author-derived synthesis identified three linked capability layers. First, longitudinal and multimodal resources – including EHRs, omics, imaging, sensors, and person-reported data – provide an informational basis for risk estimation and individualized interpretation. Second, validation, relevance filtering, accountable escalation, professional workflow, and person involvement are needed to convert information into an appropriate action. Third, interoperability, governance, privacy protection, workforce capacity, continuity across settings, equity, and economic evaluation condition whether that action can be repeated safely and sustainably. Although evidence relevant to each layer appeared across the reviewed material, the layers were not evaluated as a connected system; no source tested whether data resources, decision-to-action processes, and implementation conditions function together to produce sustained health benefit. The three-layer organization is therefore an author-derived synthesis, not an empirically tested model.

The inferential boundary was consistent across initiative types. Convergence among component studies, research resources, reviews, guidance, and product descriptions can identify capabilities and missing links, but it cannot establish that all ten 10PH dimensions are necessary, sufficient, measurable, or superior to a smaller framework. Successful operation in one cohort, specialty, product, or national data environment also cannot establish transferability. The reviewed evidence therefore supports 10PH as an author-proposed requirements map for organizing further inquiry, not as a validated integrated model. A key research priority is to test defined relationships between principles within specific use cases, tracing the pathway from data and validated interpretation through pertinent action and accountable delivery to clinical or wellness outcomes, harms, participation, equity, and costs. Until such evaluation is available, the feasibility, effectiveness, safety, equity, and cost-effectiveness of integrated 10PH remain unestablished.

4. Discussion

4.1 Interpretation of the evidence landscape

The reviewed evidence depicts movement toward continuous, person-centered, digitally enabled precision health and wellness, but not a unified model in routine practice. Public-sector and population-scale research resources assemble genomic, phenotypic, and longitudinal data; cohort and wellness programs combine repeated multimodal measurements with interpretation or coaching; remote monitoring can connect reported data to a clinical response; and official sources describe person-facing interfaces and data connections in selected products [9, 20, 23, 26, 28]. Research infrastructures support discovery rather than continuous care, bounded clinical programs do not establish transferability, and official product descriptions do not demonstrate safety or effectiveness.

For 10P-Health (10PH), the most defensible interpretation is integrative rather than comparative. The ten P-principles are interdependent: the Predictive and Personalized/Precision P-principles require the Pertinent P-principle and a Preventive or Proactive response; the Participatory and Privacy-Preserving P-principles condition legitimate use; and the Pervasive and Permanent P-principles depend on the Platform-Based P-principle. Evidence is more developed for separate capabilities than for their connections within a complete health pathway. In the reviewed material, no source evaluated how representative data, validated inference, pertinent action, accountable professional workflows, meaningful person participation, and sustained follow-up function together or whether their combination improves clinical or economic outcomes. The relationships drawn between these sources and 10PH are therefore author-derived interpretations, not validation of the framework or evidence that it is preferable to earlier formulations. This gap highlights the need for research that examines how relevant principles interact in defined use cases, rather than inferring integrated benefit from the presence of separate components.

4.2 Responsible integration, autonomy, and safety

Turning data into useful support requires more than connectivity. Interoperability must preserve meaning, models need use-case-specific validation, and outputs need uncertainty communication, actionable thresholds, and an identified responder. Digital-twin reviews describe variable definitions and early maturity, while professional adoption is shaped by infrastructure, workload, training, and organizational support [8, 13, 14, 25]. World Health Organization guidance places autonomy, safety, transparency, accountability, inclusion, and human oversight at the center of AI for health [16]. Accordingly, any use of person-facing AI within 10PH should support interpretation and escalation rather than autonomously diagnose or treat; responsibility for alerts and clinical decisions must remain explicit. These safeguards therefore need to be evaluated as part of a connected operational pathway, rather than inferred from the presence of an individual technology, validation step, or oversight policy.

The Privacy-Preserving dimension is a governance requirement, not only a security function. Individuals need understandable choices about which data are used, for what purpose, by whom, and for how long, with proportionate access and workable withdrawal. Continuous monitoring may generate false alerts, false reassurance, anxiety, unnecessary follow-up, professional burden, and overmedicalization. Public-attitude research documents concerns about privacy, errors, burden, over-reliance, and over-treatment, while the prevalence and severity of adverse outcomes remain poorly characterized [24, 31]. These are risks to measure, not outcomes demonstrated for 10PH.

4.3 Participation, equity, trust, and implementation priorities

Participation should mean influence over decisions and data use, not passive data contribution. Representation in a research resource does not itself establish influence, service access, or equitable benefit. Evidence on regulatory and health-technology-assessment processes, population genetic screening, and public attitudes toward monitoring shows that participation, digital access, privacy concerns, and trust

vary across settings and populations [12, 15, 19, 31]. Trust depends on understandable explanations, contestability, accountability, and credible choices. Equity requires representative validation, accessible design, affordability, non-digital alternatives where needed, and analysis of distributed benefits, burdens, and data risks.

Implementation research should begin with a defined use case, comparator, and explicit measurement-to-response pathway, specifying how relevant 10PH principles are operationalized and connected in that context. Evaluation should examine the pathway as a whole, combining clinical or wellness outcomes with model performance, person-reported outcomes, safety, alert burden, autonomy and privacy, workflow effects, participation, equity, and costs; where feasible, studies should also investigate which components and interactions contribute to observed benefits or harms.Vendor-described products require independent evaluation and continued verification as functions change. Policy should enable standards-based exchange and accountable governance without assuming one architecture fits every setting. Economic assessment should include implementation and maintenance costs, perspective, time horizon, budget impact, uncertainty, and distributional effects; current precision-medicine and digital-health evidence cannot establish the value or affordability of integrated 10PH [32–35].

4.4 Limitations

This structured narrative review was interpretive and non-exhaustive. Searching was limited to PubMed, IEEE Xplore, Google Scholar, supplementary searching, and English-language material, so non-English, unpublished, local, or differently indexed sources may have been missed. Although geographic contexts were noted where relevant, geographic representation was not a predefined focus of this review, no comprehensive country-level inventory was compiled during source selection. The findings therefore illustrate selected contexts rather than provide a systematic overview of the geographical distribution of the literature or a comparative assessment of national healthcare systems. Since national data infrastructures, governance arrangements, financing, and care-delivery structures may enable or constrain different components of 10PH, further research should examine these contextual differences more systematically. Narrative selection and synthesis involve judgement, and source selection was conducted within the framework-development team without review by an independent external reviewer. The evidence base combined conceptual publications, empirical studies, reviews, guidance, program descriptions, and vendor sources without formal quality scoring. These materials answer different questions and cannot be treated as one evidence level. Product information changes rapidly, commercial or unpublished systems may be incompletely described, and several initiatives lack independent evaluation. The evidence concerns components and implementation conditions rather than 10PH as an integrated intervention; it cannot establish feasibility, effectiveness, safety, equity, cost-effectiveness, or transferability. Because 10PH was developed within the author team, selection and interpretation may favor coherence with it. Separating source-reported findings from author mapping reduces, but does not remove, this risk.

5. Conclusion

This structured narrative review identified population-scale data infrastructures, longitudinal multimodal programs, remote-monitoring workflows, and vendor-described functions of selected person-facing AI products as capabilities relevant to the continuous, person-centered, digitally enabled precision health and wellness vision associated with 10P-Health (10PH). It also identified interoperability, governance, privacy, professional workflow, participation, equity, safety, and economic assessment as requirements for implementation and evaluation. These capabilities and requirements remain fragmented across resources, clinical programs, guidance, and product descriptions.

Within the reviewed material, no source evaluated 10PH as an integrated intervention. Component evidence therefore cannot establish its feasibility, effectiveness, safety, equity, or cost-effectiveness.

A key next step is to complement component-level research with prospective, independent evaluation of defined use cases that examine how relevant 10PH principles operate together across an end-to-end measurement-to-response pathway. Such studies should specify the comparator and implementation context and evaluate not only clinical or wellness outcomes, but also model performance, safety and harms, autonomy and privacy, professional workload, meaningful person participation, access and equity, and costs. This research should test explicit configurations and interactions rather than assume that all ten principles are necessary or sufficient in every setting.

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Conflict of interest

Georgi Chaltikyan originated the 10P-Health framework examined in this article and serves on the editorial board of the special issue of Journal of Applied Interdisciplinary Research. The authors declare no other conflicts of interest.

Data availability

No new primary data were generated or analyzed. This review is based on the published literature and publicly accessible official sources cited in the article.

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Appendix 1. Search strings

1. PubMed (2013-2026, 2,436 results)

(„10P-Health“[Title/Abstract]
OR „10P Health“[Title/Abstract]
OR „digital precision health“[Title/Abstract]
OR „P4 medicine“[Title/Abstract]
OR „P5 medicine“[Title/Abstract]
OR „precision health“[Title/Abstract]
OR „precision medicine“[Title/Abstract]
OR „personalized medicine“[Title/Abstract]
OR „personalized healthcare“[Title/Abstract]
OR „predictive medicine“[Title/Abstract]
OR „predictive health“[Title/Abstract]
OR „preventive health“[Title/Abstract]
OR „personalized prevention“[Title/Abstract]
OR „participatory health“[Title/Abstract]
OR „proactive health“[Title/Abstract]
OR „pervasive health“[Title/Abstract]
OR „platform-based health“[Title/Abstract]
OR „platform based health“[Title/Abstract])
AND
(„digital health“[Title/Abstract]
OR eHealth[Title/Abstract]
OR „e-health“[Title/Abstract]
OR telehealth[Title/Abstract]
OR telemedicine[Title/Abstract]
OR „health information systems“[MeSH Terms]
OR „electronic health records“[MeSH Terms]
OR „digital twin“[Title/Abstract]
OR „digital twins“[Title/Abstract]
OR „artificial intelligence“[Title/Abstract]
OR „machine learning“[Title/Abstract]
OR wearables[Title/Abstract]
OR „remote monitoring“[Title/Abstract]
OR „patient-generated health data“[Title/Abstract]
OR „patient reported outcomes“[Title/Abstract]
OR interoperability[Title/Abstract]
OR FHIR[Title/Abstract]
OR openEHR[Title/Abstract])
AND
(implementation[Title/Abstract]
OR infrastructure[Title/Abstract]
OR interoperability[Title/Abstract]

OR governance[Title/Abstract]
OR privacy[Title/Abstract]
OR security[Title/Abstract]
OR consent[Title/Abstract]
OR workflow[Title/Abstract]
OR scalability[Title/Abstract]
OR sustainability[Title/Abstract]
OR reimbursement[Title/Abstract]
OR financing[Title/Abstract]
OR „economic evaluation“[Title/Abstract]
OR „cost-effectiveness“[Title/Abstract]
OR „Feasibility Studies“[MeSH Terms]
OR „Program Evaluation“[MeSH Terms]
OR „Cost-Benefit Analysis“[MeSH Terms]
OR „Health Policy“[MeSH Terms])
AND (2013:2026[pdat]) AND english[Filter]

2. IEEE (2018-2026, 1,460 results)

(„precision medicine“ OR „precision health“ OR „personalized medicine“ OR
„digital health“ OR „P4 medicine“ OR „10P Health“ OR „10P-Health“)
AND
(„digital twin“ OR „artificial intelligence“ OR „machine learning“ OR
„internet of medical things“ OR IoMT OR wearable OR „remote monitoring“ OR
FHIR OR HL7 OR openEHR OR interoperability OR „federated learning“)
AND
(healthcare OR clinical OR patient)
AND
(implementation OR architecture OR infrastructure OR scalability OR
governance OR privacy OR security OR feasibility)

3. Google Scholar (2013-2026). Six strings were run separately, and the top 50 relevant records returned by each string were screened.
1 - main feasibility / implementation search
„precision medicine“ OR „precision health“ OR „digital precision health“ „digital health“ implementation governance interoperability feasibility sustainability
2 - 10PH / P4 / conceptual framework search
„10P Health“ OR „10P-Health“ OR „P4 medicine“ „digital health“ framework implementation feasibility
3 - health-data ecosystem / governance search
„health data ecosystem“ OR „European Health Data Space“ „digital health“ governance interoperability privacy consent implementation
4 - economic feasibility / reimbursement search
„precision medicine“ OR „digital health“ „economic evaluation“ reimbursement sustainability implementation feasibility
5 - platform / infrastructure search
„digital health platform“ OR „health information system“ interoperability governance scalability implementation precision medicine
6 - resource-sensitive implementation
„digital health“ implementation feasibility „low resource“ OR „resource constrained“ precision medicine governance interoperability

Building Digital Literacy in Health: About a Hen, an Egg and Why Usage is Not Understanding

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ABSTRACT

Digital transformation in healthcare is often equated with the widespread use of digital tools such as apps, wearables, electronic health records, and artificial intelligence–based systems. In this narrative, patients and citizens are frequently framed as users of technology rather than as competent actors whose understanding, confidence, and judgment ultimately determine whether digital health solutions are trusted and effective. However, usage alone does not constitute digital literacy. This short commentary argues that meaningful participation in digital health requires a broader understanding that integrates health literacy, data literacy, and digital literacy into a coherent framework, explicitly centered on patients and citizens and their ability to act competently in digital health contexts. Drawing on insights from a session at the DigiHealthDayS-2025, this paper explores why awareness, trust, and a shared language are currently the weakest links in digital health transformation. Using the metaphor of the "hen and the egg", we describe how patient- and citizen-led initiatives can close the circle from understanding data to building digital competence and confidently using digital tools. Reflections from audience discussions highlight persistent gaps in awareness and trust, despite high levels of access and usage. The commentary concludes that digital literacy must be understood as a shared societal responsibility and a prerequisite for sustainable digital health innovation, rather than as an optional add-on or individual skill.

KEYWORDS

Digital literacy, health literacy, data literacy, patient participation, digital health, digital competence

Introduction

Digital health is advancing rapidly, and with it the assumption that populations are ready to participate simply because digital tools are widely available. Smartphones, health apps, wearables, and artificial intelligence-(AI-)supported services have become part of everyday life for many patients and citizens. Yet this visibility of technology masks a deeper problem: widespread usage is often mistaken for understanding, and patients and citizens are assumed to be digitally competent simply because they interact with digital systems on a daily basis. At the DigiHealthDayS-2025 in Pfarrkirchen, the session "Building Digital Literacy – Patients and Citizens Leading the Way" addressed this disconnect. The

[*] *SESSION – Building Digital Literacy – Patients and Citizens Leading the Way. Host: Birgit Bauer (Data Saves Lives Germany).*

discussion was grounded in a simple but powerful metaphor: the relationship between the hen and the egg. Data literacy initiatives may start as the egg, but without a broader digital and health literacy ecosystem—the hen—the circle remains incomplete. This commentary reflects on that session and argues that digital literacy in health must be built around patients and citizens—their competencies, questions, and lived experiences—rather than around tools, if digital transformation is to be trusted and sustained.

Key Considerations

Digital Literacy is not Access, but Awareness

A recurring theme during the session was the misconception that being "online" or using multiple health apps equates to being digitally literate. Many patients and citizens described themselves as digital simply because they used technology, while simultaneously expressing uncertainty, misconceptions, or blind trust in digital outputs. Participants openly acknowledged relying on apps, smartwatches, or AI tools without understanding how these technologies work, what their limitations are, or how data are processed and reused. Digital literacy therefore goes beyond technical access. It requires awareness of why, when, and how digital tools should be used, as well as an understanding of their potential risks and benefits.

Participation Fails without a Shared Language and Trust

Another critical issue is the gap between expert discourse and public understanding. Digital health discussions are often conducted in highly technical language that excludes large parts of the population. As several participants noted, this mirrors long-standing challenges in medicine, where professional jargon can prevent meaningful patient engagement. Without clear, accessible explanations and transparency about intentions and consequences, trust cannot develop. Digital transformation fails when people feel left behind or overwhelmed by complexity.

Patients and Citizens as Co-Creators, not Target Groups

From the perspective of Data Saves Lives Germany (DSL DE), patient and citizen involvement must be understood in the context of real-world behavior and capabilities. Patients and citizens are highly curious and actively use digital health tools, often experimenting with apps, wearables, and AI-based systems on their own initiative. However, this use frequently occurs with limited digital and data competence. As a result, misinterpretations, unrealistic expectations, and, over time, mistrust toward digital health solutions can emerge.

At the same time, patients and citizens are still insufficiently involved in the development, evaluation, and decision-making processes surrounding digital health technologies. Co-creation is often discussed rhetorically, but in practice remains limited or symbolic. This gap is reinforced by a lack of accessible, transparent, and understandable information that would enable people to form informed opinions and judgments. Without deliberate efforts to explain how digital health solutions work, why data are used, and what this means for individuals, meaningful co-creation cannot occur.

Patient-driven initiatives such as Data Saves Lives Germany (DSL DE) and educational formats developed within the european digital health academy (edha) illustrate how building competence and providing clear, human-centered explanations can reduce misinterpretation, foster trust, and enable patients and citizens to contribute as informed partners rather than passive recipients.

Future Directions

Future digital health strategies should prioritize building patient and citizen competence before formal participation mechanisms are introduced. Rather than introducing involvement mechanisms prematurely, stakeholders should invest in education and dialogue that enable people to understand data use, digital tools, and health information in context. This includes developing plain-language resources, fostering cross-sector learning environments, and embedding literacy as a form of infrastructure within digital health systems.

In response to these needs, the european digital health academy (edha) is currently developing digital learning modules designed to create accessible learning opportunities for patients and citizens. Emerging directly from discussions such as those at the DigiHealthDayS-2025, these lessons aim to translate complex digital health concepts into understandable, practical knowledge. As a grassroots initiative supported by an advisory board that includes people living with chronic diseases, the edha seeks to strengthen competence, build trust, and encourage active engagement with emerging digital health formats.

Policy makers, developers, researchers, and educators all share responsibility for creating conditions in which digital literacy can grow. At the same time, patients and citizens must be supported to engage responsibly and critically with digital tools. Only through this shared responsibility can digital health innovation become both inclusive and sustainable.

Conclusion

The discussion in this special session at the DigiHealthDayS-2025 highlighted a clear message: patient and citizen digital literacy is not a luxury, but a prerequisite for trust, meaningful participation, and innovation. High levels of tool usage coexist with significant gaps in awareness, understanding, and confidence. Addressing these gaps requires moving beyond a narrow focus on technology toward a people-centered approach that integrates health, data, and digital literacy.

The hen-and-egg metaphor captures this challenge succinctly. Data literacy initiatives may start the process, but without a broader ecosystem that enables people to use digital tools consciously and confidently, the circle remains open. Building digital literacy together—through explanation, empowerment, and engagement—means investing in patient and citizen competence as the foundation for trust. This is essential if digital health is to fulfill its promise for patients, citizens, and society as a whole.

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* *Disclosure: The author is involved in the development of the cited white paper on data sovereignty..*

Generative AI in the Clinic – Hype, Hope and Reality*

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ABSTRACT

Healthcare delivery faces significant challenges and generative AI has emerged as a potential solution to these longstanding healthcare issues. The session "Generative AI in the Clinic – Hype, Hope, and Reality" invited four leading experts at the intersection of artificial intelligence and healthcare to address challenging questions regarding the actual state of GenAI in medical practice. From different perspectives, each panelist brought their unique insight: medical innovation, patient advocacy, regulatory framework, and academic evidence.

KEYWORDS

Generative AI, regulatory, innovation

Introduction

Generative AI or GenAI can be defined as a group of AI algorithms and models that are capable of producing new content, data, or solutions based on patterns and information learned from existing datasets [1]. Large language models (LLMs), a particular type of GenAI, have experienced significant growth in adoption through publicly accessible platforms such as ChatGPT, Claude, and Gemini. Notably, ChatGPT reached 100 million users just 2 months after its launch in 2023 [2].

In healthcare, GenAI debuted with bold headlines: "AI 'outperforms' doctors diagnosing breast cancer" and "Study Finds ChatGPT Outperforms Physicians in High-Quality, Empathetic Answers to Patient Questions". The potential benefits include enhanced operational efficiency, reduced administrative burden, and the prospect of "augmented" clinical practitioners.

However, that raises the question: what is hype and what is reality?

The session *"Generative AI in the Clinic – Hype, Hope, and Reality"* invited four leading experts at the intersection of artificial intelligence and healthcare to address challenging questions regarding the actual state of GenAI in medical practice.

* *SESSION – Generative AI in the Clinic – Hype, Hope, and Reality. Hosts: Lars Lindsköld and Camila Tomikawa.*

Key Considerations

Tatyana Kanvazelli opened the session by sharing her personal experience as she arrived in Munich for the DigiHealthDayS-2025 and suffered a medical emergency. She described her five-hour odyssey through the German healthcare system involving multiple offices, unclear directions, language barrier, and a literal hunt for a church to pay a deposit. Despite receiving good medical care, the visit unveiled massive inefficiencies. Tatyana Kanvazelli then reimagined and contrasted the same visit with GenAI assistance, which could orchestrate the entire patient journey across borders, systems, and languages, transforming healthcare from a fragmented maze into a coordinated experience.

Rudolf Wagner brought the regulatory perspective to the discussion, offering important context for the implementation of GenAI in healthcare settings. He noted that comprehensive AI regulation for most clinical use cases already exists, including frameworks such as the EU Medical Device Regulation (MDR), In Vitro Diagnostic Regulation (IVDR), and the more recent EU AI Act. Wagner emphasized the critical importance of patient safety and drew particular attention to emerging risks posed by LLMs operating on personal devices, which may lack the rigorous validation and safety controls required.

Martin Gerdes offered a sobering reflection on the hype and shortcomings of generative AI in healthcare contexts. He drew attention to the troubling issue of bias, noting that AI systems, by themselves, cannot mitigate or eliminate bias in healthcare applications. A major cause for bias in AI-based decision support is the lack of data representing the target patient groups, in terms of gender, age, genetic similarity, social context, and more. And he also pondered that this fundamental challenge could be addressed by the possibility of "secondary use" of live and historic health data for research purposes, as aimed for by the European Health Data Space (EHDS) [3].

Birgit Bauer brought the essential patient perspective to the discussion, underscoring the fundamental importance of AI literacy for citizens. As AI tools become increasingly integrated into healthcare, citizens must be equipped with sufficient understanding to engage meaningfully with these technologies and comprehend their implications for personal health decisions.

Finally, **Lars Lindsköld** closed the session by summarizing the key points from each panelist and emphasized what he characterized as the most critical principle underlying responsible AI adoption: the imperative that the human component must remain central and non-negotiable, even as we navigate the transformative possibilities of the generative AI era.

Conclusion

As illustrated by Tatyana Kanvazely, healthcare delivery faces significant challenges even in one of Europe's largest and most advanced economies. Generative AI offers potential solutions to these longstanding healthcare issues. However, this potential cuts both ways because the same powerful capabilities that promise to transform healthcare for the better also carry potential risks of, for example, perpetuating biases, compromising patient data, and exacerbating existing inequalities. This dual nature warrants regulatory frameworks as detailed by Rudolf Wagner. Equally critical is the continuous, rigorous examination of evidence emphasized by Martin Gerdes. Last but not least, Birgit Bauer highlighted that patients and citizens must remain at the very center of healthcare. Consequently, it is critical to improve digital health literacy so that patients can understand the capabilities and limitations of AI tools and meaningfully advocate for their own care.

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