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Review

Healthcare in Asymmetrically Smart Future Environments: Applications, Challenges and Open Problems

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Abstract: The Internet of Medical Things (IoMT) offers promising ways to meet healthcare needs of patients recovering in their own homes and other environments. Interconnected and resilient smart systems offer innovative and cost-effective ways of supporting patients by capitalizing on available devices and networking infrastructure. However, future environments will not be uniformly smart, and there will be asymmetries where our environments' (home, work, etc.) resources and capabilities differ. Technological solutions will need to adapt to such asymmetries and provide high-quality service and equitable healthcare. This article presents a systematic mapping study that explores opportunities and challenges in building next-generation IoMT smart systems for future environments. The study spans academic literature published in the decade from 2011 to 2021, profiling it from three distinct perspectives: Smart Systems, Future Environments, and Tech-Assisted Health. Each perspective was explored via a Domain Expert-Driven Systematic Mapping protocol to establish where the research is focused and to identify research gaps. From an initial search of 495 studies, 113 were mapped to a set of predefined ontology classes, spanning 6 strategic focus categories. The mapping identified sensing technologies for medical vitals and sensor fusion technologies to combine measurements for more complex analysis, cloud platforms, and connectivity challenges; health conditions that have received the most attention in healthcare smart systems; issues and opportunities in handling large data volumes in integrated smart systems; as well as security and privacy challenges. We find that future middleware frameworks will require a greater degree of interoperability and maturity to fully deliver value. Promising middleware and integration frameworks will require significant adaption and refinement to coexist effectively with current healthcare technologies. Privacy and security are critical factors in healthcare but are currently poorly supported by IoT infrastructures, especially across multiple environments.

Keywords: Tech-Assisted Healthcare; Internet of Medical Things (IoMT); smart systems; Smart Future Environments

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1. Introduction

Medical establishments and smart homes are embracing innovative technologies offered by the Internet of Medical Things (IoMT). The IoMT is a distributed, connected infrastructure of health systems, services, medical devices, and software [1]. *Smart Systems*, in the context of this article, refer to (generally) IoMT solutions that comprise specialized or ubiquitous hardware and software embedded within a patient's environment(s) to provide healthcare support. An example would be a system that tracks a patient's heart rate using a smartwatch and alerts a nurse if anomalies are sensed.

Patients interact with smart systems in their environments, such as in their homes and workplaces. By connecting these systems seamlessly into medical IT infrastructure, healthcare providers seek to provide better patient outcomes at lower costs. This promises to improve the efficiency of healthcare delivery, driving better workflow management and streamlining clinical practices by engaging and empowering patients [2,3]. Our current and *future environments* include hospitals, neighborhoods, offices, public spaces, and homes. These environments are *asymmetric* because they often do not contain the same infrastructure and cannot host the same set of smart systems. For example, a patient's home may have myriad specialized devices to help monitor or manage complex health conditions, but their workplace may only feature generalized devices like smartwatches or commercial virtual assistants like Apple Siri or Amazon Alexa. In some cases, patients with the same healthcare needs may not have the same devices within their homes due to economic or location differences. Such asymmetries can make access to healthcare inequitable.

As the IoMT becomes ubiquitous, several opportunities and challenges arise. Exchanging information between clinicians and post-operative patients who are recovering at home becomes feasible. However, the health sector imposes unique demands on patient monitoring [4] that are not always addressed comprehensively by current smart systems [5]. Healthcare systems generate high volumes of data that must be exchanged reliably while complying with the stricter levels of security and privacy demanded by complex medical regulatory regimes [6]. The data are also safety-critical in many situations, requiring low latency and a high degree of reliability where monitoring and remote care are being provided for vulnerable individuals.

In this article, we explore technological interventions and challenges that can help provide more equitable healthcare through smart systems in asymmetric future environments. This research was therefore framed by two primary questions:

RQ1: How well do current smart systems support remote patient monitoring and healthcare needs?

RQ2: What are the opportunities and challenges in building effective smart systems for healthcare in asymmetric future environments (home, office, public spaces, etc.) to achieve effective and equitable healthcare?

RQ1 is focused on understanding the current state of the art, whilst **RQ2** explores the differences in infrastructure between environments patients are likely to inhabit in the near- to long-term future. We conducted a systematic mapping study, guided by domain experts in smart healthcare systems, to answer these questions. We mapped the academic literature published since 2010, profiling it from the three distinct perspectives shown in Figure 1. *Smart Systems* encompass technological infrastructure, including software that captures, processes, and responds to events that can assist a patient in their environment. *Future Environments* describe the places and infrastructure that patients inhabit, such as hospitals, neighborhoods, offices, and homes. The final category, *Tech-Assisted Health*, relates to conditions and interventions from the perspective of medical professionals, with a focus on the evidence of effectiveness and positive health outcomes through technological solutions, or Ambient Assisted Living (AAL) [5,7]. However, we restrict the overall scope of this article to conditions, interventions, and evidence effectiveness given in the studies we found, and we do not delve comprehensively into medical standards and measures. This decision is partly to ensure that the paper remains focused more on the technological aspects of the topic but is also due to the technology-focused composition of our team of experts.

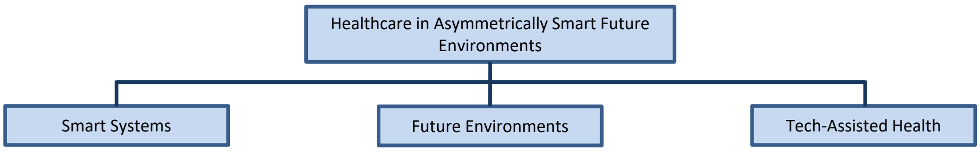


Figure 1. The three primary healthcare perspectives explored in this study.

The findings and contributions of this study include identifying key sensing technologies used in Smart Systems, middleware platforms and connectivity aspects, health conditions that have received the most attention, issues with processing large volumes of data in future systems, ways to measure the effectiveness of Smart Systems in healthcare, and security and privacy challenges faced as we build future Smart Systems in healthcare. The study highlights the benefits that large-scale adoption could provide as well as possible ways to deal with the accompanying challenges.

The rest of this article is organized as follows. Section 2 provides a deeper background into the three categories and discusses the asymmetric nature of the IoMT infrastructures that are evolving. Section 3 outlines the Systematic Mapping Study (SMS) protocol this study adopted and the ontological categories created. Section 4 then discusses the studies returned from the search queries, classifying and mapping them according to the categories defined in the SMS protocol. Finally, Section 5 presents the conclusions and implications from the mapping for further research to address the gaps uncovered.

2. Background Perspectives on Asymmetric Healthcare

2.1. Smart Systems in Healthcare

Mobile Healthcare (MHealth) is a large and growing market but faces challenges such as high data volumes and symmetries in underlying infrastructure. In 2019, the sector was already worth USD 40 billion and was expected to grow at 29% per annum for a decade [8]. Healthcare has become one of the largest industries in medium-developed and advanced economies [9]. Healthcare environments are, by their nature, asymmetric: they are characterized by collections of multi-tiered systems that differ widely in scale, cost, and capabilities [10]. High volumes of information are exchanged between practitioners and their patients, by both manual and electronic means. Some of these data are also made available to funding entities such as healthcare insurers and research agencies [11,12]. However, much of these data are siloed within disparate medical establishments and are often difficult to share between clinicians and providers [13,14]. This informational aspect of asymmetry should be considered alongside its technological characteristics.

Smart Systems or IoMT-assisted healthcare can deliver significant benefits. Managing cardiovascular diseases, dementia, chronic diseases, and post-surgery patient care can all be streamlined or optimized through Smart Systems and deliver economic efficiencies in trillions of dollars as well as save thousands or even millions of lives per year [15–18]. Most clinician and patient interactions within the healthcare system involve the use of medical equipment and electronic devices [3,6]. Figure 2 summarizes the classification categories used to map the Smart Systems perspective in this study. This perspective captures the role of sensors, actuators, and the processing required to make use of them. These represent the core technologies that allow IoMT devices to interact with patients within their immediate environments. Individual devices need to be located on the network by being *discoverable* [19] by both other connected IoMT devices and the middleware integration platforms that support them [17,20].

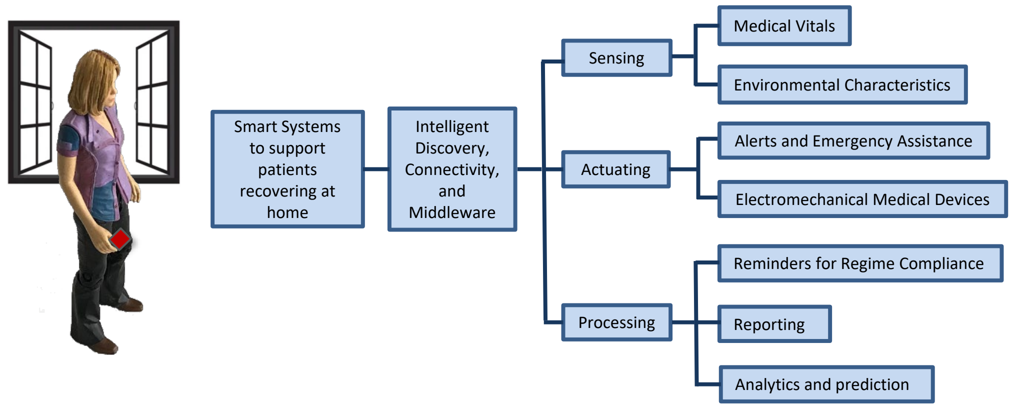


Figure 2. Characteristics of the Smart Systems perspective.

2.2. Smart Systems

Devices employed within the IoMT differ widely in scale, complexity, and cost. The term IoT originated in 1999 during discussions at Procter & Gamble that focused on self-identification technologies including Radio-Frequency Identification [21]. Developing IoMT systems for specific healthcare needs poses significant challenges for both regulators and medical technology (MedTech) companies. Standards such as ISO 30141 Internet of Things Reference Architecture [22] reflect the depth of research and cooperation required to facilitate interoperability between manufacturers [7].

European MedTech companies currently manufacture and distribute over 500,000 different pieces of equipment [23,24]. However, not all of these devices can exchange data with external systems, and many of those employ proprietary protocols [6,25–27]. This complicates the integration tasks required to support multiple disparate devices within a common ecosystem [28]. Alter [29] also challenges the use of the term "smart" in relation to the IoT and IoMT. The term is often applied too loosely, since not all of these technologies or devices meet the criteria for being smart. Alter comments that the primary smartness criteria should include the ability to learn as well as exhibit self-adaptive behaviors.

Sensing and actuation occur on the edges of an IoMT network. However, the quality and integrity of the data are highly dependent on the implementation of the devices capturing the information and the skills of the patients who operate the equipment [30]. This also leads to asymmetric disparities in the IoMT due to the maturity and capabilities of the devices, the users, and the architecture of the initiatives. At each point on this continuum, the cost is a significant driving factor [31,32].

2.3. Future Environments

Figure 3 illustrates how healthcare systems are characterized by infrastructure and technologies that operate across host environments [26,33]. Built environments [34] are infrastructure created for people to live and work in, as opposed to natural environments, such as forests and lakes.

Current built environments are evolving as innovative smart technologies are implemented to help manage them. They are referred to as Smart Future Environments [35], providing spaces where post-operative patients can employ appropriate and cost-effective Smart Systems technologies to assist in their recovery. These environments are characterized by sustainability, efficiency, and interconnectedness. They are composed of various overlapping domains and layers. Figure 3 shows how both private homes and healthcare facilities rely on critical communication infrastructure to connect them and exchange information. The network connectivity, in turn, relies on a dependable electricity supply. These connections help clinicians monitor their patient's progress and help the patient self-monitor. The three broad categories examined in this study consider how the infrastructure aspects in the middle column bridge the private home Future Environments on the left with the healthcare facilities on the right. While Figure 3 describes the characteristics of the emerging environment from a theoretical perspective, this article examines some of the current gaps between theory and current practice that may impede progress.

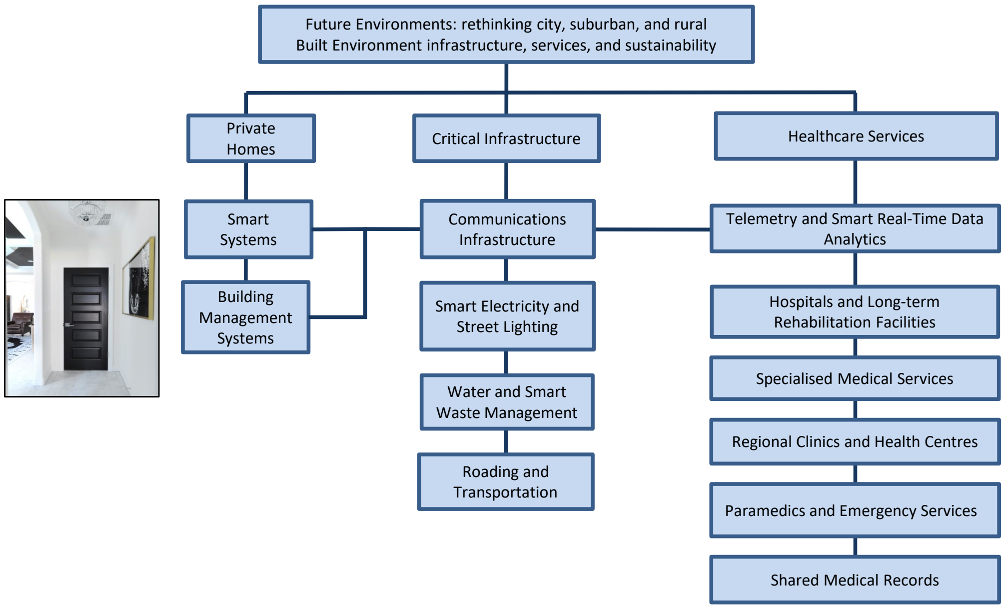


Figure 3. Characteristics of the Future Environments perspective.

Patients often rely on public transportation to visit centralized healthcare facilities or regional outpatient clinics. Emergency services and ambient support workers depend on the same infrastructure to support patients in their homes. However, what is really known about the future of our cities? What lessons have been learned from the current city-wide challenges at global scales, such as the COVID-19 pandemic? Our Future Environments should be designed, built, and maintained based on highly data-driven platforms. This will allow them to become smarter in the sense of being context-aware, use resources more efficiently, and be more agile in the way they respond. The embedded smartness in our future built environments, from city to neighborhood and building scales, is no longer primarily restricted to the environmental dimensions. Recent literature implies the transition to user-oriented implementations. This allows practitioners to draw more attention to the ultimate and ever-changing needs of the end users of our environments. Thus, from green and sustainability agendas to digital, smart, and health-related visions, the focal point for such future-oriented implementations should be based on user-centered design and technological approaches.

The move to form healthy, intelligent, and sustainable cities is now a full-fledged and widespread approach that is progressing globally. While such advancements are primarily propelled by various drivers, namely climate action commitments, the ultimate anticipated outcome of these movements is to enhance the quality of life. One of the key aspects of this methodology is the provision of equity to users with diversified capabilities. Making provisions for elderly and disabled residents is an example of one of the key categories here. From the other end, the United Nations has clearly outlined its scope by developing a framework consisting of 17 key Sustainable Development Goals (SDGs) [36]. This research emphasizes SDGs 3 (Good Health and Well-Being), 10 (Reduced Inequalities), and 11 (Sustainable Cities and Communities). To materialize sustainable cities, resilient societies need to be formed, which can only be operational by ensuring that a range of facilities, including appropriate healthcare and monitoring systems, are made available to the entire body of the society. Sustainability and security are, therefore, vital aspects of the services needed to support such environments [2,30]. Technologies such as Smart Street Lighting [37] operate at all scales, while Intelligent Building Management [38] is needed to facilitate safety, regulate indoor climates, and provide both access and security at the dwelling scale.

2.4. Tech-Assisted Health

Figure 4 details the categories of the mapping study for categorizing examples of the delivery of healthcare assisted by technologies across connected environments.

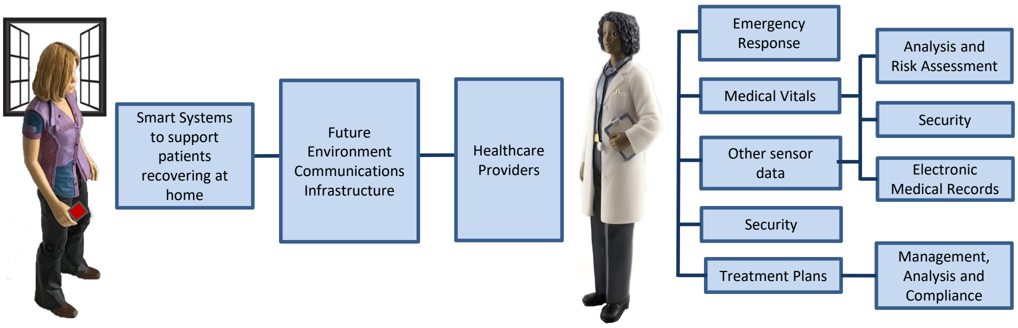


Figure 4. Characteristics of the Tech-Assisted Health perspective.

This perspective focuses on higher-level initiatives that draw together resources from the Smart Systems and Future Environments perspectives to profile patient interactions at all levels of the healthcare systems. This includes tech-enabled protocols for monitoring, complying with recovery regimes, and emergency response interventions. At a higher level, it considers the motivating factors that drive or impede the socio-technical aspects of the IoMT [31,39]. Patients often want to recover in their own, familiar, home environment after surgery. The IoMT offers a way to provide a degree of remote monitoring and interaction that satisfies both the desires of the patient and the duty of care the clinicians provide [40].

Mwangi et al. [41] illustrate the value of Tech-Assisted Health in neighborhood and home environments in their study of asthma management in Rwanda. During the cold season, asthma claims thousands of lives, often due to chronic asthma attacks where the sufferer cannot get assistance quickly enough from emergency services. The authors' mobile application allows users to call for help from their immediate neighbors in the community using a single button press on the mobile app. The first responders are often asthma sufferers themselves, so the initiative encourages and empowers an empathic community involvement. The cost of providing and supporting such a service is low; hence, it can be scaled across communities easily. While other technologies are often impractical from a cost perspective, mobile smartphones are a key driver in African economies [42]. Such programs are therefore highly suited to these types of communities.

3. The Domain Expert-Driven Systematic Mapping Study Protocol

The research protocol chosen for this study factored in the diverse domain expertise and experience of the authors. This is a multi-disciplinary team whose research interests intersect at the three key perspectives outlined in Section 2. They share cross-disciplinary research at AUT, collaborating across the research laboratories that focus on IoT and IoMT software development, hardware engineering, and Future Environments. Figure 5 shows the systematic mapping protocol the team adopted for this study.

A systematic mapping study protocol is a formal method of building a classification scheme and data structure to map the areas of interest in a research field [43,44]. Mapping techniques are used to extract a representative set of studies from a larger pool of possible candidates by defining appropriate inclusion and exclusion criteria. The categories are then used to record the focus of each study, leading to an understanding of what has been achieved. By using a combination of infographics and summary tables, the perspectives that emerge in the maps show where practitioners are focusing their research efforts and indicate where the gaps in the current research lie. The analysis of different combinations of categories then helps to answer specific research questions posed during the earlier stages of the mapping protocol. Research maps are designed to be coarse-grained to show where the research activity is concentrated without evaluating experimental results in depth or considering designs [45]. However, once the desired research outcomes are identified during the design of the study, clear research questions help to determine the depth of the analysis that will be needed.

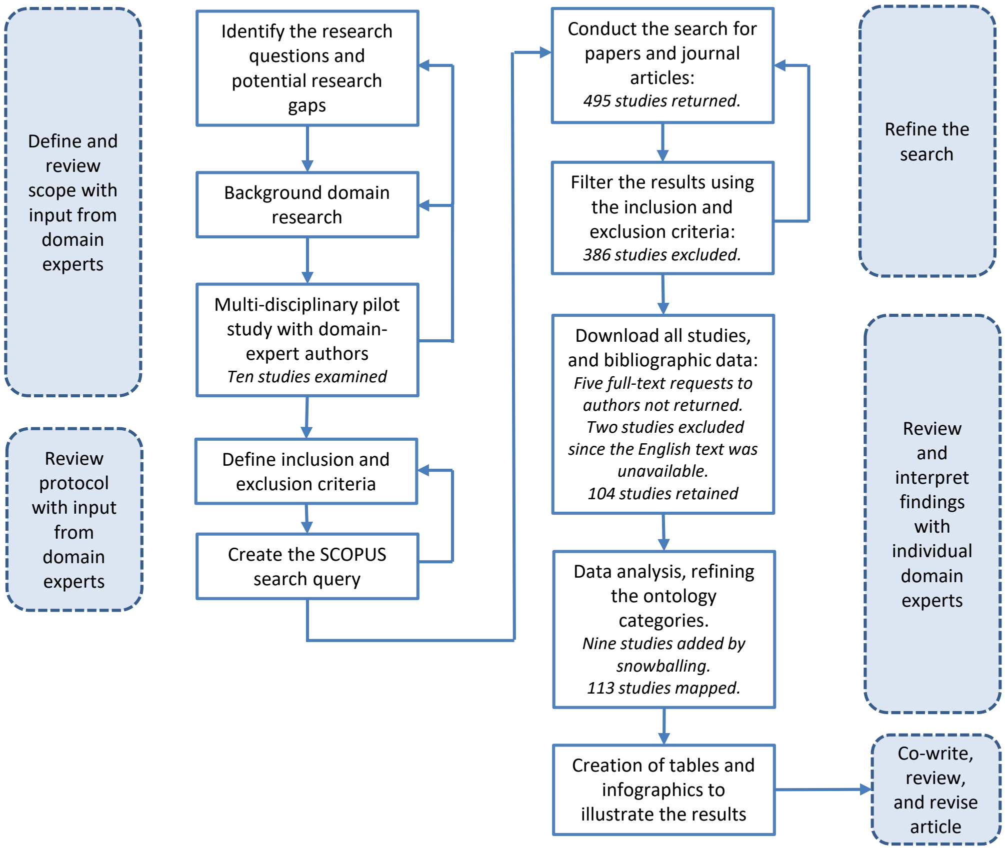


Figure 5. The domain expert-driven systematic mapping study protocol adapted from Haghighatkhah [46] and Petersen [43,44].

The protocol steps were adapted from Haghighatkhah et al. [46] and Petersen et al. [43,44]. This combination of approaches divided the process into two distinct stages. The first began with planning and goal identification. The scope was reviewed regularly as each author shared perspectives from their domain. These regular co-review tasks are detailed in the blue boxes beside the protocol steps. The scale and complexity of the healthcare environment quickly became evident during the pilot study that was conducted. This was based on a set of studies that provided cross-domain background knowledge. Each author contributed sets of significant studies from their domains of expertise to identify and highlight key concepts and technologies needed to frame the research questions properly.

The resources identified included Verma [47], who describes the cyber-physical characteristics of IoMT devices in smart city environments. This study defines five distinct levels of device operations, ranging from the most basic interactions with equipment at a patient's bedside through to system-level data exchange where health records are managed. The socio-cyber-physical aspects of the acceptance of technologies are presented to highlight some of the barriers to adoption. A study by Laplante [48] then provided a structured approach to describing IoMT applications, while Alter [29] discussed making sense of "smartness" in the context of smart systems and smart devices.

Figure 5 emphasizes the iterative nature of this stage. Regular reviews ensured that the inclusion and exclusion criteria were appropriate and that the ontology categories reflected accepted domain terms. SCOPUS was chosen since it enables repeatable, bi-directional traces of citations to and from the contributing databases. The SCOPUS extraction tools enabled the query result to be downloaded into Excel™ tables easily for quick quality analysis reviews. In practice, this ensured that less time was spent removing duplicates, and searches could be refined iteratively. The query returned 495 studies during the 10-year period, including conference papers, journal articles, and book extracts. A "COVID" restriction term ensured that, amid the COVID-19 pandemic, epidemiology-focused clinical studies that included terms such as "home" and "IoT" or "IoMT" were not returned. This removed 24 studies from the set. The most significant refinement was limiting the search to the SCOPUS MEDI medical area rather than including software engineering or a broader scope. A search without this restriction returned 2891 studies. Many of those studies included medical terms in their index keywords but did not focus on healthcare as their primary topic. The queries used to create the final set of studies were published on Mendeley Data [49].

The next phase dealt with conducting the mapping, extracting the data after downloading the full text of each study and the required bibliographic information. Five lead authors were contacted, since their studies could not be located via the SCOPUS Articlelinker or in other databases. None of these studies were received. A further two studies were excluded, since they were not available in English.

An in-depth mapping was performed by reading each article in full to capture occurrences of the classification categories found. Data were extracted to a Microsoft® Excel™ spreadsheet that captured ontology classes in columns for each study [50,51]. All categories were grouped into one of the following broad classifications:

Condition or Intervention: This identifies the patient's post-operative condition that they are recovering from, such as bariatric surgery or a kidney transplant. It also classifies longer-term conditions such as home care for diabetes, dementia, or AAL.

Sensor Type: This category captures the types of sensors discussed in the study, such as pulse oximeters for determining a patient's oxygen saturation, temperature and humidity measurements, as well as specialized saline or movement sensors and accelerometers.

Electromechanical Actuators: Kidney dialysis requires the control of pumps and microfluidic equipment. Other types of actuators control airflow for sleep apnea as well as trigger alarms when abnormal conditions occur.

Platforms and Connectivity: The studies describe a wide range of platforms and technologies to support the connections between all tiers in the IoMT. These include Cloud, Fog, RFID, and custom protocols running on mobile smartphones, wearables, and "nearables", the discrete devices that are not worn on the body but operate close to the location of the patient.

Future Environments and Smart Buildings: Most of the studies briefly describe the context of the environment their interventions operate within. These can include scales such as hospital, suburban, neighborhood, building, or dwelling locations. Many initiatives operate within combinations of these environments.

Study Characteristics: The stated scale, reported maturity of the techniques, the depth of their healthcare provider integration, and indicative costs were captured if the study provided them. This section also identified the use of big data, artificial intelligence, and machine learning as discussed in the studies.

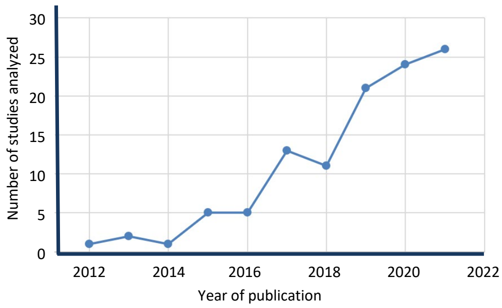
The final list of 104 studies was refined by snowballing to add additional relevant studies from references cited in the studies. The resultant mapping showing the classification data is available for download from Mendeley Data [49]. The choice of presentation infographics and table structures was agreed upon during subsequent reviews. This reflects the collaborative nature of multi-disciplinary teams, drawing on their shared experience of previous mapping studies and techniques that they have found to be appropriate in their past publications.

4. Mapping and Analyzing the Findings

We now present our overall findings and provide some answers to **RQ1** and **RQ2**. Section 4.1 provides quantitative insights. Section 4 refers to sensing and sensor fusion techniques and challenges. Section 4.3 explores middleware platforms and connectivity solutions and challenges. Section 4.4 looks at how specific health conditions are being monitored. Section 4.5 discusses key technologies used in addressing large data volumes through all levels of Technology-Assisted Health. Section 4.6 discusses the maturity of the studies we reviewed, showing that significant challenges remain in developing robust solutions. Section 4.7 highlights the security aspects as the key problem area to address when new technology solutions are created. Finally, Section 4.8 covers other challenges not discussed in preceding sections.

4.1. Quantitative Findings

Figure 6 presents the distribution of the publications mapped for this study. The analysis showed that 84% of the studies were published between 2017 to 2021. Section 4.2 notes the wide use of the IoMT via smartphones, where mobile apps or mobile data are reported in 60% of studies. This may show a weak correlation with the surge in the availability of highly capable smartphones after 2014 as reported by Statista in their Global Smartphone Shipment Analysis [52]. The mapping suggests that, from 2017, mobile devices began to be perceived as a more viable platform for IoMT research, providing a ready-made, low-cost platform with integrated sensors and communications. The use of custom wearables further augments mobile devices, providing additional sensors to capture characteristics such as blood pressure and heart rate [53,54].



Publisher	Number of publications
IEEE	42
Elsevier	11
Springer	10
JMIR	6
MDPI	4
ACM, Wiley, Taylor-Francis and other venues	31
Other Open Access	39

Figure 6. Mapping the publication dates and the distribution of the study publications.

The publication venues and the number of studies published in the years 2017 to 2021 are shown in the right-hand table in Figure 6. MDPI featured as the largest open access publisher (4%). A total of 39 peer-reviewed open access studies were published across a wide range of independent sites (35%). Open access represented 39% of the studies mapped.

4.2. The Application of Sensors and Actuators within Environments

Medical vitals or *Vitals* are defined as the four indicators of life. They include body temperature, pulse rate, breathing, and blood pressure [55]. Vitals can be captured directly from the patient within their environments through sensors. The analysis of this data is performed either locally or after transmitting readings to an external third-party or health provider system. The IoMT relies on balancing the processing load imposed on its often resource-constricted, low-powered devices by distributing the computational tasks across other nodes in the network. Actuators can then be instructed to respond to these, assisting by sounding alarms, opening medicine dispensers, or activating other equipment.

Figure 7 shows the percentage of studies that discuss each device or condition and some of the infrastructure that supports them. The percentages add up to more than 100% since most studies discuss more than one sensor type, leading to overlaps in the category analysis. The use of sensors and actuators was classified according to the criteria defined by Beckman et al. [56]. They describe three broad categories:

- Medical body sensors that are fitted close to the individual, either as external devices or implants. These include heart rate monitors that apply techniques such as electrocardiography (ECG) and photoplethysmography (PPG), SpO_2 pulse oximeter sensors for oxygenation, wearable clothing, and smart adhesive skin patches.
- Environmental sensors that sense characteristics such as air quality, air pressure, room temperature, CO_2 levels, and humidity near the patient.
- Localization sensors that determine the position of individuals within the premises or the location of a building within a neighborhood. This information is especially useful during emergencies. Localization can rely on either Body Sensor Networks (BSNs) or building infrastructure network devices.

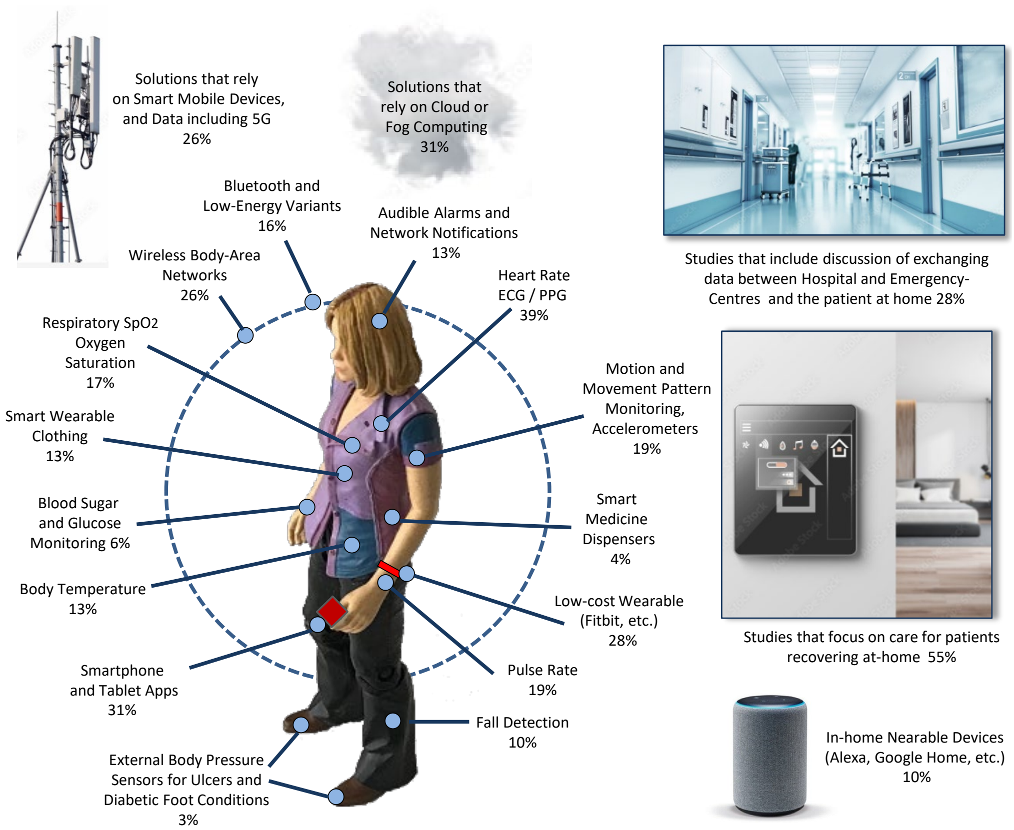


Figure 7. The application of sensors and actuators to capture medical vitals and conditions, the platforms, and how they are connected.

These classifications are primarily differentiated by how closely the IoMT devices are fitted to the patient's body or distributed within the space the patient is occupying. They can also be classified by the way they exchange and transfer data, either capturing and storing it locally for later retrieval or transmitting it in real time.

Nearables are devices that occupy the same physical space as the rehabilitating patient [56]. Unlike smart wearables, such as fitness trackers or blood pressure monitors, they are not attached to the patient's body [12,15]. Nearables can include specialized custom devices that sense a patient's movements [26,54,57] or commercial devices such as Amazon Alexa™ and Google Home™. Nearables are also able to form ad hoc networks to allow them to collaborate, extending the range of in-home localization services for patients. This was discussed in the context of the AAL (20%) [54,58,59] and dementia care studies (6%) [60–62].

Continuous monitoring of sensors was discussed in 17% of the studies. Intermittent monitoring consumes less power and was described by 5% of the studies [63]. However, real-time monitoring is vital if the condition being watched can become life-critical.

Sensor Fusion: Beckmann et al. [56] explain that combining data from multiple different types of sensors, referred to as *sensor fusion*, leads to more personalized and accurate patient interventions. It also increases the number of possible sensors that could be chosen to address a patient's needs. A typical example is cardiovascular monitoring for heart conditions, which featured in 33% of the studies. ECG readings, coupled with blood pressure, SpO_2 pulse oximeter readings, and body temperature, help to capture a more balanced view of the patient's condition than a single sensor would alone [64–66]. Hatcliff et al. [67] describe *clinical sensor fusion*, where sensors can communicate with medical application platforms directly in hospitals or emergency rooms. This is primarily used to capture a patient's vitals. In contrast, *remote sensor fusion* is used to facilitate *telemedicine* or *telerehab*, where the IoMT devices provide sensor information from patients rehabilitating at home. Liang et al. [68] further delineate sensors by the types of events that trigger them. These include *direct* or *proximal* stimuli captured directly from the patient and *indirect* triggers based on changes in the patient's environment that may affect their condition. Examples of indirect stimuli could include an increase in pollen counts that lead to asthma attacks [41,69] or changes in humidity or room temperature [11,19,70]. Mwangi et al. [41] provide a counterexample of this exhibited by asthma patients who are exercising in a gym. Their increase in heart rate and increased breathing exertion do not necessarily indicate a critical asthma event. Such situations demand that the sensor fusion must be context-aware so as not to trigger false alerts.

4.3. Platforms and Connectivity within Future Environments

Sensors or mobile devices attached to or worn on the body communicate via Wireless Body-Area Networks (WBAN) and Wireless Sensor Networks (WSN) (26%). These are the enablers of the BSNs discussed earlier. IEEE Standard 802.15.6-2012 codifies short-range wireless communications in the vicinity of or inside the human body [71]. Shahzad et al. [72] discuss network protocols in the context of health systems integration, while Touati et al. [73] outline the Open Service Architecture for Sensors (OSAS) [74]. This protocol describes how low-powered devices worn by the patient communicate through base-station gateways in the home. Beckmann et al. [56] further explain the role of the OSAS architecture in standardizing the integration of incompatible devices from multiple vendors. The studies describe how network gateways can be augmented with the use of mobile smart devices [54,68,75], referencing generic networking standards such as IEEE 802.11-2012 [76]. Examples include the discussion in Devedzic et al. of ingestible and implantable device communications [7] and in Lai et al. [19], discussing the role of short-range, low-power device communication.

Fog or Cloud data exchange featured in 31% of studies. In the context of the IoMT, Fog computing is defined as the decentralized distribution of data stored in larger Cloud servers to smaller network servers hosted individually within neighborhoods [77]. Fog servers in the IoMT can include small custom devices installed locally in homes to provide data storage and processing on a smaller scale to the regional health provider Cloud services. Other neighborhood Fog infrastructure can extend the range of these platforms [78]. This targeted distribution of processing and storage offers opportunities to scale the IoMT in innovative ways [15]. However, data stored in public clouds present a target that may be exploited by malicious parties [79].

The remote edge network environment of the patient that IoMT devices operate within is a significant contributor to the observed asymmetries. Pramukantoro and Gofuku [80] explain that the performance and reliability of low-powered connections can vary widely, since they are affected by the patient's environment. Hospital environments often have high densities of devices, while the patient's own home can introduce obstacles that block wireless telemetry, especially for wearable devices [81]. Holmes et al. [82] explain that a Received Signal Strength Indicator (RSSI) level of −70 db is the minimum for low-latency data exchange. Signal strengths below −80 db have proven to be unreliable. Since wearable technologies rely on this infrastructure, poor reception and transmission compromise their effectiveness [70,83].

Compatibility and interoperability remain significant challenges for vendors of typical low-powered network devices. Pyattaev et al. [81] show that, in high-density environments, low-energy Wi-Fi channels fail to operate efficiently when supporting more than 20 simultaneous users or devices in close proximity. Calvillo-Arbizu et al. [5] note that IoMT devices need to be uniquely addressable if the data they accumulate are to be reliably classified, analyzed, and tied back to the patient they were captured from. Network topologies are dynamic; hence, techniques for facilitating reliable IoMT operations rely on appropriate choices of network architectures, composition, protocols, and data standards. However, there was no evidence in the studies of the application of established IoT architectural standards, such as ISO-30141 [22], in the Internet of Things Reference Architecture.

4.4. Addressing Patient Conditions with IoMT Devices

Table 1 details sensors (including sensor fusion) and actuators applied to specific patient medical conditions encountered in the studies. The most widely encountered condition discussed in the studies, cardiovascular disease, highlights the reliance on medical vitals exhibited repeatedly in these studies. The primary diagnostic tools for cardiovascular conditions are electrocardiographs (ECGs) and photoplethysmography (PPG) [84]. PPG sensors are the main sensor type used in smartwatches and wearables [85]. ECG and PPG readings, coupled with oxygenation, blood pressure, and body temperature, were the sensor combinations discussed most extensively in cardiovascular studies.

Table 1. Application of sensors and actuators for specific conditions or interventions.

Condition or Intervention	Study Percentage	Sensors and Actuators Used	References
Cardiovascular and heart monitoring, including angina and hypertension.	33%	ECG/PPG, SpO_2, blood pressure, pulse, temperature, accelerometers.	[11,13,15,20,63–67,69,80,86–111]
Ambient Assisted Living (AAL) for the care of the elderly, including movement monitoring.	21%	ECG/PPG, SpO_2, blood pressure, pulse, temperature, accelerometers, smart medication dispensers.	[40,53,54,58,59,62,82,83,86,88,106, 112–123]
General psychological well-being, support, and care.	12%	Indoor localization, smart microphone movement detection, medication dispensers, CO_2 level monitoring, blood pressure, temperature, urine monitoring, emotion detection.	[8,17,26,40,53,64,118,119,124–128]
Sleep disorders and monitoring for sleep apnea.	11%	Accelerometers, SpO_2.	[13,14,60,63–65,82,115,119,127, 129]
Fall detection.	10%	Indoor localization, smart microphone detection, pulse, ECG/PPG, movement monitoring.	[53,54,68,72,82,83,119,120,123,130]
Medication reminders and plan compliance, including exercise regimes.	8%	Indoor localization, reminders, medicine dispensers.	[72,87,113,124,131]
Chronic disease management at home.	7%	ECG, SpO_2, blood pressure, breath measurements.	[59,90,92,96,120,132,133]
Diabetes and in-home personal management of complications and conditions, such as diabetic foot.	6%	Treatment and medication reminders, glucose monitoring, accelerometers, indoor localization.	[26,27,63,70,72,134,135]
Dementia care at home, including Parkinson's and Alzheimer's.	6%	Indoor localization.	[16,57,58,60–62,64]

AAL for elderly patients living independently at home was often discussed in conjunction with fall detection [53,54,82]. General physiological and psychological well-being was a wider category that featured sensor and actuator combinations that applied to less common medical conditions. Approaches such as urine monitoring [135] provide an additional source of data to support diabetics [72]. Anderson et al. [26] discuss novel approaches to the traditional use of breath detection and odors that have characterized medical diagnosis for centuries. Gas sensors can detect acetone on the breath of people having diabetic seizures [136]. Sleep apnea event detection relies on alarms that wake up the patient as well as accelerometers and sensor fusion to constantly monitor breathing patterns during sleep periods [13].

The high volume of data generated by real-time monitoring demands sophisticated techniques for aggregating data, filtering out duplicate readings caused by network congestion, and recognizing gaps caused by lost data. For example, in one trial [5], a patient group generated 1137 ECG data messages in 30 minutes, out of which only 84 were significant. Filtering and aggregation solutions to address this issue include algorithmic pattern-matching as well as AI/machine learning [70,107] and/or multi-agent approaches [20,137]. Similarly, false positives occurring from environmental factors, such as accelerometers' sensitivity to vibrations, also require further data processing techniques [14,64].

4.5. AI, Big Data, and the Processing and Dissemination of Medical Telemetry

A total of 35% of studies used AI or machine learning to identify conditions. However, only 28% of the solutions included a connection to a remote health provider such as a hospital or emergency medical center. Consequently, many current approaches do not facilitate direct exchange and integration of data into healthcare systems. The lack of deep integration also surfaced in non-AI solutions. The issue becomes even more apparent for solutions that remotely monitor or assist patients in their personal environments (home, office, etc.) rather than in healthcare environments [86,90]. Jim et al. [14] discuss how big data analytics promise a way of managing and prioritizing the huge feeds of data that would become available if more patients were monitored remotely. However, big data are featured in only 26% of the other studies, suggesting that this is still an early-stage feature of the IoMT.

Celestrini et al. [87] describe *flow-based monitoring*, an approach to managing large volumes of patient data using algorithms and AI. Filtering, aggregation, and relevancy are often context-sensitive and often impossible to generalize [134].

4.6. The Implied Maturity of the IoMT Solutions Mapped

Discussions that focused only on the use of devices for in-home patient care were found in 55% of the studies. However, more than half of the studies presented theoretical or prototype laboratory solutions without providing deeper explanations of how they would facilitate long-term use for patient care. Table 2 summarizes the categories that were mapped to capture the implied maturity of each solution discussed. This characterization was partially based on the depth and scope of the pilot studies outlined in Section 3. The scale of the pilot study was estimated by using the number of participants and the length of the field trials they performed. The high or large criterion was assigned when a study indicated that their solution had undergone more extensive field trials or the patient count in their case study group was sufficiently large. However, only 4% reported evidence of study trials that included more than 20 patients, while 31% provided evidence that they had performed small pilot studies of 10 participants or fewer. By also considering descriptions provided of the IoMT prototypes, 60% of the studies were deemed to exhibit a low level of maturity.

While this assessment could be considered subjective, factors that contributed to this evaluation considered prototypes that described the use of bulky sensors and Raspberry Pi or Arduino platforms that cannot operate continuously without large power packs. While the prototypes produced valuable experimental results, the route to commercialization would require specialized, smaller, and more robust custom devices. Calvillo-Arbizu et al. [5] commented that integration with legacy systems remains an open challenge. This correlates with the analysis of the depth of integration reported in these studies. Only 1% of the studies discussed aspects of how the data could be used with up-stream healthcare systems.

However, it is encouraging that the indicative cost per patient was low in 44% of the studies. Only one study presented evidence of research conducted with a large-scale commercial IoMT solution with which the researchers had a direct involvement [132]. No other studies indicated the potential commercialization route for the research they had developed.

Table 2. The implied scale, maturity, integration, and indicative cost of the solutions proposed.

Study Characteristic	High or Large	Medium	Low or Small	Not Specified
The scale of the pilot study performed.	4%	10%	21%	65%
The implied maturity of the solution from the evidence presented.	3%	24%	60%	13%
The depth of the integration of the IoMT data captured into the healthcare provider's systems.	1%	10%	32%	58%
The indicative cost per patient based on the description of the proposed IoMT devices employed.	0%	17%	44%	39%

4.7. Security, Privacy, and Reliability within IoMT-Enabled Healthcare Environments

Security, privacy, and trust were discussed in general terms in many studies. However, only 3% of the studies described these aspects in their solution discussions. Hospital equipment operates within zones that must exchange data securely and reliably, with health data systems using protocols such as HL7 [138]. However, these protocols are proprietary and siloed. They do not easily extend out to operate at the edges of the IoMT in home environments. Security, privacy, and the difficulty of sharing data in ways that satisfy regulatory requirements are reflected in the low number of studies that detail exchanging data with these systems (28%). The reported depth of integration is low, with results only being shared with clinicians via custom interfaces. Therefore, most of the spending is concentrated at the large healthcare provider edges of the IoMT, not in future urban, neighborhood, or home environments.

Several works [7,124] explain that the scale of the digital data, and the fact that they comprise primarily confidential information about patients, demands that cyber-security experts and ethicists should be an intrinsic part of digital health technologies. Current solutions such as Google Home™ and Amazon Alexa™ cannot yet perform to an acceptable level of reliability and are barred from exchanging data directly with secure healthcare systems. Current regulatory guidelines require secure protocols such as HL7 [138] to meet acceptable levels of trust and security, which these ubiquitous devices lack.

4.8. Other Challenges and Open Problems

The studies highlighted a common set of challenges and open problems in addition to the security and privacy concerns outlined earlier. Calvillo-Arbizu et al. [5] discuss the data life cycle that is required to analyze and correlate readings from multiple sensors over an extended period. The challenges lie not only in the volume and timeliness of the information but also in determining if the dataset is truly representative of an individual patient's condition. Coupled with the challenges of gathering the telemetry reliably from appropriate devices, standards such as ISO-IEC-11073 highlight the complexity of IoMT device interoperability across multiple vendors [139]. Morales-Botello et al. [13] comment that remote data capture of sensor information analyzed using big data approaches is showing promise. However, while capturing continuous vital signs is well understood, more sophisticated patient models are needed to detect subtle activity-specific changes and evaluate the risks they imply. They note that understanding which physiological variables are most useful is still an unresolved gap. Each patient's condition, ranging from cancer and asthma to diabetes and obesity, presents via specific, well-defined physiological indicators. This demands that implementing a large-scale healthcare IoMT with myriad home-based sensors will require highly sophisticated healthcare patient modeling approaches, which are still in their early stages of development and application [82,95].

5. Conclusions and Future Work

The conclusions drawn by the authors were driven by the following findings and contributions from this mapping:

- Medical vitals remain the most widely accepted clinical indicators. Supplementing vital measurements with information from other sensors is desirable but remains a gap requiring further research.
- Security and privacy concerns in healthcare present different challenges from those that drive IoT implementation in other sectors.
- The benefits of wide-scale adoption for home-based recovery need to be quantified better given the indicative costs of implementing the IoMT at scale.
- It is challenging for the current IoMT implementations to provide reliable data that are not reporting incorrect or ambiguous conditions due to anomalies in sensor readings. Doing this at the scale to make it economically viable is problematic.

RQ1 asked how well general purpose mobile devices and low-cost smart sensors can provide RPM, capturing the data needed to support both long-term care and shorter-term post-operative patients recovering in their homes after surgery. Section 4 demonstrated that the range and capabilities of the sensors and their ability to capture not just vitals can, in some situations, report a patient's current condition with sufficient reliably. However, the regulatory environment, the necessary communications infrastructure, and the data processing capabilities are not well enough established yet to deliver the expected long-term benefits. The potential volume of telemetry generated by a functional IoMT presents challenges in how data will be aggregated and analyzed quickly enough and how network infrastructure can provide the reliability and robustness demanded of it.

The study revealed a high reliance on capturing medical vitals. Two medical practitioners were invited to read final versions of this study. They confirmed that they rely primarily on medical vitals and that, while other indicators are potentially valuable, especially via RPM, the lack of time and funding needed to adopt new IoMT devices is restricting their uptake. They indicated that the demands imposed by the COVID-19 pandemic has changed many aspects of their longer-term plans. These discussions have resulted in an opportunity for the authors to participate in a practical controlled evaluation of how well new sleep apnea patients adjust to using Continuous Positive Airway Pressure (CPAP) devices when they first begin using them. This later study will be published as a companion to this article.

RQ2 asked how we could adapt the information available from IoMT sensors and the data they capture to address asymmetries and achieve equitable healthcare outcomes as patients move through these environments. Section 2 noted that many studies provided a context for the medical condition they are addressing by discussing the scale and cost of providing healthcare. Hence, there is a strong incentive to address these costs using innovative IoMT approaches. The mapping showed that sophisticated and complex, and therefore often more expensive, smart technologies within the healthcare system are concentrated inside large and medium healthcare facilities. Within these environments, centralized services provide access to expensive equipment such as MRI and CT scanners as well as X-ray equipment. Home-based devices are by necessity less complex and potentially less smart than hospital-scale devices. However, their ability to correctly identify targeted conditions or events within their immediate locale presents opportunities not necessarily available within hospital environments. The scale and processing needs of an individual patient's environment are considerably less than those at hospital scale. Hence, enabling the IoMT in more home-based situations offers promising ways of targeting and addressing individual patient healthcare needs. This demands that centralized health systems must be able to consolidate, process, and respond to the additional data in a smart, reliable, and timely way.

Combinations of medical vitals appear in all the conditions categorized. This suggests that investment in low-cost, standardized vitals measurement may offer a way of facilitating baseline IoMT data capture that can be further augmented with specific sensors for individual conditions. Scaling this sufficiently presents a way of addressing the asymmetries by using more cost-effective, standardized devices and increasing their penetration into patients' homes. The studies mapped in this analysis suggest that the use of home-based MedTech devices is increasing. However, for them to see wider adoption and be able to provide valuable information, they must address the regulatory, privacy, and interoperability issues highlighted in this study.

The SCOPUS search query was designed to exclude studies that focused on COVID-19. Coronaviruses affecting humans (HCoVs) were evidenced historically by mild illnesses. Since there is mounting evidence that SARS-CoV-2 has become endemic, a revised mapping study, once sufficient research studies are available, would be a valuable contribution. In these situations, monitoring vitals remotely becomes a critical factor in controlling the spread of disease. The evolving landscape of asymmetric healthcare and conditions such as COVID-19 that force patients to recover in isolation will create new opportunities for the IoMT to support home-based care more effectively. In doing so, it will address the asymmetric concerns identified in this study in more constructive ways.

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