Healthy but at Home: A Taxonomy to Structure the Opaque Remote Patient Monitoring Market

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Abstract

The Covid-19 pandemic has resulted in overburdened hospitals and patients' inability to access appropriate healthcare services. In inpatient care, patients are being monitored for extended periods of time, especially in the case of emerging diseases, further straining hospital capacities. According to current literature, Remote Patient Monitoring Systems (RPMS) can help address and reduce this burden. However, in practice, RPMS adoption has been slow. We argue that there exists a lack of transparency in the current RPMS landscape which results in a mismatch between RPMS offerings on the market and users' need for these systems. Aiming to structure the opaque RPMS market, we develop a taxonomy that describes the characteristics and nuances of RPMS based on 39 existing systems. Drawing on the taxonomy, we derive five archetypes that help both practitioners and scholars to differentiate between system types and thus support future RPMS deployment to improve healthcare accessibility and quality.

Keywords: Remote Patient Monitoring Systems, Taxonomy Development, Health Information Systems

1. Introduction

The fading Covid-19 pandemic has ruthlessly highlighted that our capacities to treat, heal, and support citizens in times of health crises were not sufficient. Naturally, the aim of increasing these capacities is constrained, among other reasons, by the limiting factor of physical space. Solutions that relieve the burden on hospitals while simultaneously ensuring continued high-quality care of patients, therefore, appear to be increasingly important (McCabe et al., 2020). Appropriate discharge and follow-up of patients is a pivotal component in this effort. When critical patients are discharged, the possibility of disease exacerbation remains beyond the hospital stay (Li et al., 2020). Diagnosed disease conditions may worsen due to a lack of observable health metrics. Conversely, if hospitalized patients are retained despite being healthy, valuable hospital resources for those in need of urgent care are sacrificed. Therefore, the question of how to overcome this conundrum of continued inpatient treatment versus discharge arises.

Generally, telemedicine systems offer a starting point to address this trade-off. Telemedicine enables the provision of healthcare services over a physical distance by employing information and communication technology (ICT) (Bashshur, 1995). As a subform of telemedicine, so-called remote patient monitoring systems (RPMS) provide a means of communication between physicians and patients. To this end, RPMS leverage ICT to enable location-independent transmission of health information (Vegesna et al., 2017). Thereby, RPMS facilitate the monitoring of patients' physiological data and vital signs at a distance and, consequently, can help prevent diseases or their exacerbation, and ultimately reduce fatalities (Malasinghe et al., 2019). Using RPMS can help physicians gain access to information that would otherwise have been available only on-site. In hospitals, in addition to the reduced risk of infection, the number of patients cared for could be dramatically increased. At the other end of the interaction, despite the physical distance, patients can conveniently benefit from receiving medical care and monitoring at home. Consequently, RPMS can help build humanitarian resilience to address health crises.

Recent literature suggests that RPMS are fundamentally operational and provide value to address healthcare challenges during health crises such as the Covid-19 pandemic (Aalam et al., 2021; Annis et al., 2020; Chen et al., 2020). Gordon et al. (2020) conclude that "RPM for Covid-19 provides a mechanism to monitor patients in their home environment and reduce hospital utilization." However, despite these insights, RPMS are not being widely employed in practice

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(Seshadri et al., 2020; Witte & Zarnekow, 2019). Rather, it appears that traditional, non-digital solutions continue to be implemented preferentially. We argue that a necessary step to promote the use of RPMS and eventually leverage their potential to improve healthcare overall is to obtain a clear understanding of the current landscape of existing RPMS. In particular, it is necessary to explore whether there is a gap between currently existing systems and actual user needs, and to identify opportunities to leverage existing solutions to address the challenges described above.

To achieve this objective and inform both research and practice, we argue that the following tasks need to be performed: (i) firstly, it is necessary to perform a comprehensive analysis and classification of existing systems. In doing so, key characteristics of RPMS can be identified, thus enabling the comparison of system specifics and the demands imposed on these systems and the healthcare providers using them (e.g., during crises). (ii) Secondly, disentangling the characteristics of existing RPMS is imperative. This allows us to provide an overview of whether (and, potentially, how) particular RPMS lend themselves in establishing resilience for different use cases. Moreover, overarching categories provide practitioners with an overview of how RPMS are currently being applied in practice. A comprehensive understanding of existing system categories thus paves the way for the purposeful exploitation of RPMS. We therefore address the following research question: *Which dimensions characterize existing RPMS and what superordinate archetypes of RPMS currently exist on the market?*

To answer the research question, we conduct a two-stage research project. First, based on 39 existing RPMS, we develop a taxonomy following the methodology described in Nickerson et al. (2013) and extended in Kundisch et al. (2022). Second, we perform cluster analysis based on this taxonomy to identify five superordinate archetypes of RPMS. Our findings contribute to literature and practice in various ways. We highlight that the existing market in its current form only partially meets the needs for addressing health crises. In particular, we suggest that the lack of post-discharge RPMS in practice is a limiting factor to their use in critical healthcare services. The five identified archetypes *Fast AI-powered Reporting Devices*, *Non-AI-powered Reporting Devices*, *Disease Surveillance Apps*, *Hospital-at-Home Platforms*, and *Disease Surveillance Platforms* provide practitioners with a preliminary way to identify areas of application. Future research can leverage these archetypes to uncover differences in their intentional use and identify pivotal acceptance criteria to facilitate practical application of RPMS.

2. Remote Patient Monitoring Systems

As noted above, RPMS are a form of telemedicine that describe technologies which collect health-related information at a patient’s defined location (e.g., at the patient’s home) and transfer the resulting data to a healthcare provider that analyses and derives recommendations based upon the data. The ultimate goal of RPMS is to deliver healthcare to patients’ homes and overcome the spatial distance between healthcare professionals and patients (Singh et al., 2011; Vegesna et al., 2017).

The patient data transmitted to the healthcare provider can include, for instance, patients’ vital signs or information regarding the subjectively perceived wellbeing of patients. Such information can be obtained via systems that are developed especially for these use cases, such as sensors for vital sign measurement or more interactive solutions like questionnaires embedded in mobile applications. Usually, the resulting data is patient generated data, e.g., health-related data like symptoms, lifestyle choices, and treatment history but also biometric data obtained via third party devices or even consumer wearables like smartwatches (Abdolkhani et al., 2019). The main feature of patient generated health data is that the patient is primarily responsible for collecting the data and therefore is much more involved in their own healthcare journey. Thus, their role is more active, which might in turn lead to a higher acceptance of the proposed treatment (Hirsch et al., 1972; McInnes, 1999). Overall, the usage of RPMS brings numerous advantages. First, the quality of healthcare can be increased due to closer communication between patients and their healthcare providers. Second, medical resources can be used more efficiently and in a more cost effective way (Iranpak et al., 2021). Third, RPMS use allows treating patients without the need for physical contact, which is especially useful during pandemics but also for the treatment of contagious diseases in general since it eliminates the risk of infection (Aalam et al., 2021; Taiwo & Ezugwu, 2020).

RPMS also enable hospital-at-home use cases which experienced increased relevance during Covid-19. Due to the limited number of available hospital beds and scarce availability of health monitoring systems, innovative solutions were required (Casale et al., 2021). The hospital-at-home concept aims to achieve hospital-grade surveillance of patients’ health metrics in order to bring a level of quality of healthcare to patients’ homes that they would otherwise receive in inpatient care only. Certified medical-grade RPMS enable hospital-at-home use cases by reliably providing healthcare professionals with the same high-quality data used within hospitals. This facilitates reducing the time a patient would normally spend in a hospital (early supported discharge) or avoiding hospitalization completely (admission avoidance) (Boone & Shammash, 2022; Iranpak et al., 2021). Thereby, these applications contribute to saving hospital resources, enable a reduction of the burden on the healthcare system, and make its operation more efficient. In the long term, this reduction of pressure is needed to conquer the challenges caused by an aging, multimorbid society, and the resulting increase in patient numbers. But also from a more short-term perspective, in situations like the Covid-19 pandemic which led to skyrocketing patient numbers, these applications improve quality of care and could even save lives due to more efficient triage procedures. Finally, more efficient follow-up care can lead to fewer readmissions after a patient is discharged from the hospital, again resulting in reduced pressure on the healthcare system and improved overall quality of care.

3. Methodology

3.1 Taxonomy Development

This paper aims to provide a comprehensive classification of existing RPMS in the form of a taxonomy. Taxonomies enable researchers to study the relationships among concepts in order to hypothesize about these relationships (Nickerson et al., 2013). This allows to structure and organize existing knowledge in the field. To develop our taxonomy, we follow the method proposed by Nickerson et al. (2013) as well as the extensions provided by Kundisch et al. (2022).

The development process comprises several steps that we will describe in the following. First, we describe the object of analysis, the target user groups and the intended purpose. The object of analysis are existing RPMS. Our target user group are actors in the healthcare domain, especially organizational decision-makers in institutions that provide healthcare (e.g., hospitals). The purpose is to identify configurations of RPMS that are beneficial for promoting health(care) in general, and humanitarian resilience in crisis situations in particular. Based upon the purpose of the taxonomy, we define the meta-characteristic of this taxonomy as “characteristics that shape the monitoring of patients at the intersection of outpatient and inpatient care”. We apply the subjective and objective ending conditions proposed by Nickerson et al. (2013) after each iteration to determine whether an additional iteration is required.

As described in Nickerson et al. (2013), each iteration in the taxonomy development process follows either the empirical-to-conceptual (E2C) approach or the conceptual-to-empirical approach (C2E). In the E2C approach, initially, a set of objects to be classified needs to be determined. Then, the researcher determines common dimensions and characteristics along which these objects can be classified and that are a logical consequence of the meta-characteristic described earlier. In the C2E approach, on the other hand, the researcher conceptualizes the dimensions without referring to the objects to be classified. Rather, this approach is based on existing knowledge, experience and individual judgment of the researcher (Nickerson et al., 2013). Afterwards, the selected dimensions and characteristics are to be aligned with the objects to identify whether every object exhibits exactly one of the characteristics in each dimension. Additionally, characteristics should vary across objects since a characteristic shared by every object provides no additional value even if it is derived from the meta-characteristic (Nickerson et al., 2013).

(1) For the first iteration, we followed the C2E approach. To build and increase our knowledge base, we identified extant scientific knowledge using a literature review following the methodology proposed in Webster and Watson (2002). In accordance with this procedure, a keyword search was carried out, and the identified literature was evaluated regarding its relevance for this research (Webster & Watson, 2002). We constructed a search string to identify scientific publications containing the phrases “remote patient monitoring”, “telemonitoring” or “remote health information system” within title, abstract or keywords. The resulting search string was then adapted to different scientific databases that were used for the literature search (i.e., EBSCO Business Source Complete, ProQuest ABI Inform, Association for Information Systems eLibrary, and ScienceDirect). As a result of the analysis of the identified literature, the following two dimensions were added to the taxonomy in the first iteration: *Temporal* and *Communication* characteristics. Since the ending conditions for the taxonomy development process were not met, we performed an additional iteration.

(2) For the second iteration, we followed an E2C approach. The focus in this iteration was the identification of real-word RPMS. To identify RPMS, we used the Healthskouts database. This database contains information on 257 medical products. After eliminating all non-relevant products, 22 RPMS were deemed relevant for the taxonomy and analyzed for dimensions and characteristics. Dimensions added during this iteration were *Key Technology* and *Primary User*. Again, objective ending conditions were not fulfilled because, among others, new dimensions were added to the taxonomy. We therefore performed an additional iteration.

(3) For the third iteration, we again employed the E2C approach. In order to build on a broader spectrum of RPMS, the business platform Crunchbase was searched with the search string “remote patient

monitoring" which returned 25 results. After eliminating already included and non-relevant results, 14 new objects were added to the taxonomy. Based on information retrieved from the providers' websites, we identified the following additional dimensions: *AI*, *Medical Device Certification*, *Application Area*, *Video Conferencing* and *Targeted Disease*. Due to the addition of new dimensions during the third iteration, the objective ending conditions were not met, hence an additional iteration was performed.

(4) In the fourth and last iteration of the taxonomy development process, we again employed the E2C approach. For this iteration, we used the search string "remote patient monitoring" in a Google search which led to the inclusion of an additional three objects in the taxonomy. To access an overview of the complete list of RPMS that our taxonomy is based upon, we refer the reader to the online appendix. Because, after the fourth iteration, every ending condition was met, the taxonomy development process is terminated after the fourth iteration and the taxonomy is complete (see Table 1).

3.2 Cluster Analysis

To identify higher-level RPMS archetypes based on the empirical results of our taxonomy, we decided to use cluster analysis. The aim of cluster analysis is to form groups of objects where the similarity between the objects within each group, i.e., cluster, is maximized, while the similarity between objects of different clusters is minimized (Everitt, 1980). Thus, the result of cluster analysis is a collection of heterogeneous groups of objects with homogeneous objects within these groups (Huang, 1998). Following recent IS research, e.g., in the domains of blockchain or conversational agents (see Bachmann et al., 2022; Diederich et al., 2022), we conducted a two-step approach based on Punj and Stewart (1983).

First, we apply the Ward method to determine the optimal number of clusters. This method employs a bottom-up approach where, initially, every object has its own cluster (Anderberg, 1973). Subsequently, the two nearest neighbors (objects or clusters) are combined into one cluster; this process is iteratively repeated until one single cluster is obtained which contains all objects (Mojena, 1977). We further applied the elbow criterion (James et al., 2021), Mojena's (1977) test, and a content-specific analysis to determine the optimal number of clusters. Our results, weighing complexity and explanatory power, indicated an optimal number of five clusters. For the second step of the cluster analysis, Punj and Stewart (1983) suggest using the k-means algorithm. However, this procedure relies on interval or ratio scaled input data and is therefore inappropriate for nominal scale categorical data (Chaturvedi et al., 2001). Since our taxonomy describes data exclusively with categorical values, the k-modes algorithm was chosen instead. This clustering algorithm works similar to the k-means algorithm, but uses modes instead of the means, thereby overcoming the application issues of k-means in the case of categorical data (Huang, 1998). To perform the k-modes cluster analysis, we used R, version 4.0.5.

4. Results

4.1 Taxonomy

We present our final taxonomy in Table 1 and describe the dimensions of the taxonomy in more detail below.

Application Area: This dimension refers to the main use case of the system. RPMS can be applied for different activities along the patient journey. The taxonomy distinguishes between five different characteristics. *Hospital-at-home* systems enable patients to stay at home even though they have conditions that, in the absence of RPMS, would have led to their hospitalization. Thus, hospitalization can be avoided completely in cases where it was necessary before. An object characterized as *post discharge* is used primarily for the surveillance of patients after hospitalization has ended. These systems enable healthcare providers to discharge patients earlier and, therefore, reduce the burden of inpatient treatments by splitting them into inpatient and outpatient treatment where possible, thereby reducing patients' length of stay. The characteristic *disease detection* applies to RPMS which are primarily for patients without symptoms. These systems are used to identify diseases before the onset of symptoms to enable an early start of treatment by the healthcare professional. *Disease surveillance* systems, on the other hand, are used in cases where a patient is already diagnosed with a disease and information about the status of the illness is required to allow for optimal treatment (e.g., to monitor medication effects). Finally, the fifth characteristic of the dimension application area is *other*. Systems characterized as such often serve a more general purpose and thus, the other characteristics of the dimension cannot be applied.

Targeted Disease: This dimension defines whether the categorized object is designed for a specific (type of) illness. First, the characteristic *cardiac diseases* summarizes all illnesses regarding the heart, such as atrial fibrillation, heart attacks, and heart failures. The characteristic *cancer* includes all types of cancer that might be monitored, such as breast cancer, lung cancer or any other type of cancer. Next, we identified the characteristics *diabetes* and *sleep apnea* which capture

RPMS designed specifically for the monitoring of these diseases. The characteristic *gait* describes systems designed for illnesses related to gait, walking disorders or balance problems. Next, there is the characteristic *pulmonary disease*, describing RPMS designed for the surveillance of diseases like Asthma or chronic obstructive pulmonary disease (COPD). The last two characteristics in this dimension describe objects which are not designed specifically for one of the targeted diseases described earlier. Rather, systems characterized as *multiple* are objects which are designed for several different diseases but cannot be classified into the characteristics mentioned above without violating the principle of mutual exclusivity (Nickerson et al., 2013). Meanwhile, the characteristic *other* is applied to objects that are not designed for any of the previously mentioned disease types.

Temporal: This dimension characterizes the time difference between the collection of the patient data and the time that the healthcare provider receives the information. Systems characterized as *checkable* are used in non-time-critical situations where the healthcare provider uses the collected data but does not rely on a fast transmission of the data. On the other hand, systems characterized as *alerts* or *monitoring*, are needed in time-critical situations where a slow reaction of the healthcare provider might result in poor patient outcomes. This is potentially relevant for applications like hospital-at-home where the aim is to establish continuous surveillance of a patient's vital parameters in order to rapidly detect deteriorations in the patient's condition. In this context, the difference between the characteristics *alerts* and *monitoring* is crucial. The mere possibility of enabling push-notifications or alerts might result in more immediate reactions by the healthcare provider and thereby might result in a better outcome for the patient. Yet, a healthcare provider's constant and conscientious monitoring of patient data might result in better patient outcomes when alerts are poorly implemented and potentially ignored.

Primary User: This dimension relates to the primary user of the RPMS on the side of the healthcare provider (note that, on the patient's side of the interaction, the user is always the patient whose data is being collected). The first characteristic of this dimension describes objects developed for *family doctors or specialized physicians* like cardiologists and oncologists with their own offices. Objects which are developed primarily for healthcare professionals working in hospitals are classified into the *hospital* characteristic. Like in the first two dimensions, we include the *other* characteristic which catches all RPMS that cannot be classified into *family physician* or *hospital* characteristics.

Key Technology: This dimension describes the main technology of the RPMS. Most of the identified systems are either focusing on a single *device* which is used to measure patient information, like physiological data, or on a *platform* which is used for the representation of patient information. Finally, the third characteristic places the focus on *mobile applications*. Note that classifying RPMS into a characteristic of this dimension does not mean that the identified object only uses that specific technology, but rather that the technology focus is on that technology. For example, an object characterized as *platform* might also rely on *devices* or *mobile applications* for the collection of patient data, but does not have its focus on these devices or apps. Likewise, an RPMS that focuses on *device*-based data collection likely comes with a *mobile application* for displaying and forwarding the data measured by the respective device.

Communication: This dimension defines the type of information flow between the patient and the healthcare provider by classifying objects along either the *reporting* or the *interactive* characteristic. Since patients are more actively engaged in the monitoring process when the RPMS is classified as *interactive*, this dimension can also be understood as including a representation of the level of patient involvement. Again, however, both types of RPMS have their advantages. On the one hand, higher levels of patient involvement might result in stronger treatment acceptance because patients feel more heavily involved. On the other hand, low levels of patient involvement could lead to higher acceptance for patients who are not willing to learn how to use these systems. It is important to mention that usability is a strong factor to acceptance of a technology (Ondiege & Clarke, 2017; Shah et al., 2013). Therefore, in this context, two channels to higher perceived usability and acceptance exist: either, the system needs to have a well-implemented interaction process, or little to no interaction at all so as not to put too much strain on the users.

Artificial Intelligence (AI): This dimension is used to assess whether an object makes use of AI to realize its use case. For instance, AI could be helpful for clinical decision support systems embedded within the RPMS. Furthermore, it could reduce user workload and thus relieve the burden on healthcare providers. AI-applications in RPMS range from a notification to the patient that a doctor's visit should be arranged to a direct notification to the physician about a possible detection of illness or an early warning score regarding the patient's condition. Therefore, RPMS with AI can contribute to increasing the quality of care provided. In our taxonomy, RPMS that use AI are characterized as *AI-enabled* while those that do not employ AI are classified into the *No AI* characteristic.

Table 1. Final taxonomy

<table>
<tr><th>Dimensions</th><th colspan="8">Characteristics</th></tr>
<tr><td>Application Area</td><td colspan="2">Hospital-at-Home</td><td colspan="2">Post Discharge</td><td>Disease Detection</td><td colspan="2">Disease Surveillance</td><td>Other</td></tr>
<tr><td>Targeted Disease</td><td>Cardiac</td><td>Cancer</td><td>Diabetes</td><td>Sleep Apnea</td><td>Gait</td><td>Pulmonary</td><td>Multiple</td><td>Other</td></tr>
<tr><td>Temporal</td><td colspan="3">Checkable</td><td colspan="3">Alerts</td><td colspan="2">Monitoring</td></tr>
<tr><td>Primary User</td><td colspan="3">Family Physician</td><td colspan="3">Hospital</td><td colspan="2">Other</td></tr>
<tr><td>Key Technology</td><td colspan="3">Device</td><td colspan="3">Platform</td><td colspan="2">Mobile Application</td></tr>
<tr><td>Communication</td><td colspan="4">Reporting</td><td colspan="4">Interactive</td></tr>
<tr><td>AI</td><td colspan="4">AI-enabled</td><td colspan="4">No AI</td></tr>
<tr><td>Video Conferencing</td><td colspan="4">Supports Video Conferencing</td><td colspan="4">No Video Conferencing</td></tr>
<tr><td>Medical Device</td><td colspan="4">Certified</td><td colspan="4">Not Certified</td></tr>
</table>

Video Conferencing: The penultimate dimension refers to whether the RPMS provides video conferencing functionality. Some RPMS only enable conversations between patient and healthcare provider via text messaging. However, even though a fast reply via text message (i.e., asynchronous interaction) might result in similar effects as through a video conference, the latter provides even more immediate feedback (i.e., synchronous interaction) and enables the communication of nonverbal cues, including facial expressions. In order to distinguish between the different RPMS more clearly, this dimension therefore only considers video conferencing, using a binary classification into the characteristics *supports video conferencing* and *no video conferencing*. The resulting dimension is also in line with the meta-characteristic because video conferencing tools are an important technology used to stay connected to patients in cases where no physical interaction is possible. Thus, video conferencing helps to ensure high levels of acceptance and quality of care when changing the interaction between patient and healthcare provider from the physical to the digital realm (Taylor et al., 2015).

Medical Device: Finally, the last dimension describes whether an RPMS possesses a medical device certification (i.e., *certified*) or not (i.e., *not certified*). In healthcare organizations, this dimension can be decisive for the adoption of the respective RPMS.

4.2 Five Overarching RPMS Archetypes

To use our taxonomy for further analysis, we applied the cluster analysis methodology described above. In doing so, we identified the following five overarching RPMS archetypes based on our sample of 39 existing RPMS (percentage values in parentheses indicate the share of systems in the archetype that exhibit the respective characteristic):

Fast AI-powered Reporting Devices (n = 10) are relying on devices as their key technology (80%) with some focusing on platforms (20%) but no apps. Furthermore, artificial intelligence is leveraged most of the time (80%) and notifications are delivered through alerts (80%). RPMS associated with this archetype are often used in hospital-at-home applications (40%) while the second largest part falls on applications areas classified as other (30%). Consequently, the main users of these systems are hospitals (50%). Fast AI-powered Reporting Devices do not support video conferencing features and the most of them include a medical device certification in the US or the EU (60%). A small portion of these systems is specifically designed for cardiac health issues (20%), but most are not designed for a specific disease (70%).

Non-AI-powered Reporting Devices (n = 9) also mainly communicate their data in a non-interactive reporting manner and are similarly leveraging devices as their key technology (89%). However, as the name of the archetype suggests, they differ in the usage of AI. 89% of the RPMS in this archetype are not integrating AI at all. Regarding the temporal dimension, two thirds of the RPMS in our sample are classified as monitoring while one third is classified as checkable. The predominant share of the Non-AI-powered Reporting Devices is certified as a medical device (89%). Again, no video conferencing is supported by these systems. In contrast to the first archetype, the largest application area is disease detection (44%). The users of these RPMS are mainly family physicians or hospitals (each 44%). Moreover, besides cardiac diseases (33%), health issues regarding gait and sleep apnea are addressed in this cluster.

The archetype of Disease Surveillance Apps (n = 9) includes RPMS which are based primarily on applications for smartphones. Only one system is classified as device and the remaining two are classified as platform. While Disease Surveillance Apps are inherently interactive, most of the systems are used for monitoring (44%) and checkable (33%). Therefore, it can be argued that the temporal dimension in this cluster is mixed. Furthermore, AI is employed in two thirds of the systems contained in our sample. As a core characteristic of this archetype, 78% of the RPMS are used for disease surveillance. The main users for these kinds of systems are family physicians (67%). Furthermore, most are certified as medical devices (78%) and are designed to be used for the monitoring of various forms of cancer (44%).

Hospital-at-Home Platforms (n = 3) are generally targeting multiple diseases (100%). Unsurprisingly, most of the systems are for hospital-at-home applications (67%). Moreover, all RPMS are classified as alerts (33%) or monitoring (67%). All Hospital-at-home RPMS in our sample are certified as medical devices and make no use of AI. Additionally, most of the systems support video conferencing (67%). Due to them being designed for hospital-at-home applications, the primary users of these systems are hospitals (67%).

Finally, Disease Surveillance Platforms (n = 8) are primarily designed for disease detection (88%). Furthermore, the primary users are family doctors or specialized physicians (88%). While having a focus on reporting as their main form of communication (75%) and on platforms as their key technology (100%), no single targeted disease stands out (multiple: 50%; none: 25%). Again, most of the RPMS in this archetype are certified as medical devices (75%), even though this is the second lowest share compared with the other archetypes. A key characteristic that distinguishes disease surveillance platforms from disease surveillance apps is the latter's lack of video conferencing functionality (63% vs. only 11%).

5. Discussion

5.1 Guidance for the Practical Use of RPMS

First, our taxonomy provides governments and other institutions responsible for managing a country's humanitarian and public health with an initial understanding of the types of systems that are currently available on the RPMS market. By raising visibility of the possibilities and capabilities of the current RPMS landscape, we are paving a preliminary path to increased use of these systems in the healthcare sector. For instance, existing solutions can be evaluated for their possible adoption in practice. Moreover, by identifying the focus areas of application of RPMS, various characteristics and dimensions can be considered in the development of new systems for remote patient monitoring. Thus, our taxonomy supports future RPMS development and provides system developers with the opportunity to tailor their solutions specifically to the actual needs that they identify within their healthcare sector domain.

Second, our taxonomy illustrates that existing solutions are only partially capable of addressing the conflicting concerns of inpatient treatment versus discharge. This lack is highlighted by the fact that only 2 of the 39 RPMS examined in this research focus on the post discharge application area. Despite the urgent need of hospitals and the relevance corroborated in literature, these findings reveal a gap between adequate RPMS supply and demand. Therefore, we argue that, in order to reduce the burden on hospitals through continuous monitoring of discharged patients by means of RPMS, more adequate, targeted solutions need to be developed for and implemented in the market. In this context, we emphasize the need for increased and enhanced exchange between all relevant stakeholders to identify user needs and match them to actual RPMS benefits through specifically targeted system design. Thereby, increased levels of resilience against contemporary healthcare challenges can be achieved.

Third, the derivation and identification of overarching archetypes helps understand the purpose that existing systems are currently aiming to fulfill. It is evident that RPMS differ in the way they interact with patients, in their use of various technological capabilities, and in the scope of their utilization throughout the healthcare sector. Decision-making about the deployment of RPMS in various healthcare sectors may be guided by our classification in order to facilitate a more focused use of RPMS. In the context of overcoming health crises and establishing sustainable and resilient patient care, the identified archetypes point to initial opportunities for action.

5.2 Contributions to Literature

Our taxonomy provides three major contributions to scientific literature and research. First, to the best of our knowledge, we are the first to provide a taxonomy for RPMS. The developed taxonomy structures the current body of knowledge regarding RPMS and provides a common understanding of RPMS, in both their scope and function. Moreover, our taxonomy can be used by researchers to obtain an overview of the dimensions and characteristics that shape the respective application areas of RPMS; it supports researchers in positioning their research endeavor in this highly complex, dynamic, and unstructured domain by providing a deeper view into the topic of RPMS and the intersectoral area between inpatient and outpatient care. Therefore, the taxonomy contributes to a narrow, but specialized view on the areas of remote care and telemedicine. A deeper understanding of these research areas is needed to help researchers understand the journey from the development to the operation of such RPMS and their implementation in the healthcare sector.

Second, apart from the taxonomy itself, the classified objects show that the current view on RPMS as one system class only partially meets the different application areas of RPMS – our taxonomy suggests that RPMS vary substantially in terms of their provided functions and use case. Indeed, the derived archetypes demonstrate that the objects which are currently unified under the term of RPMS are highly heterogeneous. Moreover, the archetypes underline the importance of not differentiating RPMS by single dimensions and characteristics, but rather to analyze whole configurations of objects.

Finally, the disaggregation through the archetypes assists current and future literature in conducting more specific analyses on acceptance and requirements research. Each archetype provides researchers with distinct paths for future research and to conduct more fine-grained and tailored assessments, benefiting actual implementations in practice. In particular, corresponding results can be contrasted across the identified system types, thereby contributing to a more nuanced literature landscape.

5.3 Future Research & Limitations

Our work is subject to several limitations. First, the taxonomy includes no information about the quality of the different RPMS. Instead, during the analysis of the objects, we relied on the descriptions provided by the providers. Moreover, the coding process as well as the creation of dimensions and characteristics is subjective; other researchers might create a different taxonomy. We aimed to overcome this limitation by coding the same objects and continuously comparing results throughout the taxonomy development process.

Furthermore, we cannot rule out that we might have missed objects that would have had to be classified. It could be that some RPMS were not identified through our Healthskouts and Crunchbase search, either because they were not listed or because our search strategy did not lead to an exhaustive list of results (e.g., due to our specific selection of search terms). The addition of more RPMS could have resulted in a modified taxonomy and thus also in different archetypes (Bachmann et al., 2022). Some weaknesses of the archetypes were already discussed above. Additionally, more objects might have contributed to creating more statistically robust clusters. Future research should ensure that as many relevant systems as possible are identified in the search process by employing more nuanced strategies.

We identify several interesting avenues for future research. First, looking at the distribution of the objects' characteristics, we observe that there are some gaps, i.e., some combinations of characteristics for which no existing RPMS could be identified. To name one example, future research could elaborate on why practitioners are not implementing post discharge RPMS, investigate limiting factors and address these with potential solutions. Moreover, RPMS are currently viewed as standalone systems; researchers could identify possible use cases where multiple RPMS are connected to create an ecosystem. In this regard, the question arises whether there are synergies that could be created and exploited within such an ecosystem. Last, current research has not yet addressed the perspective from healthcare professionals and their individual requirements on RPMS. Previous work has emphasized the individual requirements of healthcare professionals on new IS artefacts (e.g., Braun et al., 2022).

6. Conclusion

Health crises highlight that hospitals reach their operational limits, especially in exceptional situations like the Covid-19 pandemic. Despite emerging literature recognizing the potential of leveraging RPMS to address these challenges, there is a yawning void in actual application. In particular, we argue that uniform transparency on existing systems and system types is lacking to address emerging challenges in building humanitarian resilience. Our taxonomy, developed based on a total of 39 existing RPMS, provides practitioners with an initial approach to identify the opportunities that are available through the deployment of RPMS. Moreover, the archetypes indicate distinct areas of application that can be addressed by RPMS. We argue that the use case of monitoring after patient discharge is particularly neglected. Our findings enable a more rigorous examination of RPMS for addressing health crises and establishing humanitarian resilience.

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8. References

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