Asynchronous Vital Sign Telemetry and Predictive Decompensation Alerts: Machine Learning Models for Enhanced Remote Patient Monitoring and Intervention

Dr. Andreas Papadopoulos, Associate Professor of Electrical and Computer Engineering, National Technical University of Athens, Greece

1. Introduction to Remote Patient Monitoring (RPM)

Remote Patient Monitoring (RPM) is fundamental to long-term and preventive care. It allows healthcare professionals the capability to observe patients continuously and anticipate their needs. This can be particularly helpful for those with chronic diseases or patients who reside in rural settings, away from hospitals with specialty providers. For many patients, RPM helps to either reduce travel to a healthcare facility, avoid admission, decrease the need for emergency care, or even reduce the length of their hospital stay because appropriate interventions occurred earlier in the process. The concept of RPM has evolved due to increasing demand from healthcare settings to intervene early in the patient care process. This trend has been aided by the encouragement of technological advancements, leading to a decrease in the costs of digital devices. The increase in mobile computing and wireless technology has also contributed to the implementation of RPM.

Triggered by the pandemic, the patient monitoring system is moving towards innovative solutions that enable continuous real-time patient monitoring without introducing inconvenience to the patient, thereby replacing the limitations of existing patient monitoring systems. Current technologies have several limitations with respect to patient monitoring. Traditional patient monitoring strategies rely on human clinicians to visit the patient's bedside to measure and interpret physical attributes of the patient. This strategy is unsuitable for continuous observation on a day-to-day timeline rather than for a short period. Furthermore, patients are unable to move freely and are confined to their beds. Machine learning models can help in RPM for enhanced patient health.

1.1. Definition and Importance

Remote Patient Monitoring (RPM) is the collection of health data of patients using digital technologies, generally over long geographical distances, which is then sent electronically to a caregiver. An RPM system typically comprises three stages: data acquisition, data processing, and data visualization, and can employ several techniques and tools, including wearable sensors, IoT devices, smartphones, wireless devices, embedded appliances, and smart features in legacy medical equipment. The increasing adoption of such monitoring systems by researchers, healthcare providers, and medical equipment manufacturers is testimony to the increasing importance and real-time relevance of patient-generated health data in research and clinical settings. RPM offers a plethora of benefits, most notable of which is increasing patient engagement in their healthcare, thereby leading to improved health outcomes, boosting communication between patients and healthcare providers, and lowering the cost of operations for healthcare providers. Daily health stats, such as heart rate, are usually collected and shared through secure digital platforms in near real time, and offer patients the opportunity to take control of their health, empowering them to be more proactive in the management of chronic conditions. RPM adoption has, however, been constrained by some challenges, including technical, financial, management change, implementation process, human resource, and policy-related issues. The adoption of AI-augmented RPM systems can go a long way in addressing some of these challenges.

1.2. Challenges in Traditional RPM

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Instead of the traditional system of health care that requires a consultation to gather patient vitals and often sends the patient on to another care provider to obtain these results, Remote Patient Monitoring (RPM) systems allow a health professional to receive reports from these self-monitored tests in real-time in the electronic medical record. The clinician is then free to act if the reported vitals are concerning or to momentarily stop and analyze reports at a later time if the room is busy. Currently, these two systems of reporting, via automated means and in the presence of a health professional, remain disjointed and inefficient from a quality management standpoint when treating a person with a chronic condition. These traditional RPM systems lacked several features that were required for advanced healthcare settings. Patients often forget to measure or report their results on a regular basis. For patients that did complete self-monitoring, all measurements were performed using non-connected devices; getting connected to patients required a separate appointment with a telemedicine coordinator or a technician, making it cumbersome and inefficient. Lastly, the patient information is reported to educators and providers via unintegrated systems separate from the electronic health record and task assignment system.

Traditional remote patient monitoring (RPM) involves static trend reports that educate future changes to the patient's plan of care. Oftentimes, reports are not reviewed in a timely manner. Reports are printed and organized for health professionals based on alert status that can limit missed items, but a report is not created if all measures are "in the green." Lastly, traditional report data may not be integrated into the electronic medical record for research and quality management initiatives. There are several challenges with traditional RPM. First, measuring and reporting are manual processes for the health consumer, which could lead to human error and inconsistency. This could affect patient safety, quality of care, and overall outcomes. Second, without real-time education and intervention, the traditional system only allows for trend analysis of historical data that can also lead to increased healthcare costs. Third, reports are not reviewed in a timely fashion, timely being defined as same-day or within 24 hours of receipt. The current algorithm takes between 1 and 7 days for a report to be reviewed, which increases potential liability and patient harm. Fourth, patients are less likely to be adherent to the reporting schedule if repeat testing is delayed. Finally, technological, physical, and emotional barriers can limit the RPM plan from being implemented. For the clinical setting, the technological barrier was the only barrier in place out of these six mentioned, which can now be overcome with technology changes. All of these challenges can decrease the quality of care, quality of outcomes, and increase health costs. Given these challenges, real-time reporting that requires essential data with an alert system was critical when developing the algorithm. It quickly identifies if an individual is outside normal parameters, which would alert the provider to assess the patient electronically or via phone. The ultimate desire is to have integrated and automated reporting in a meaningful-use certified healthcare record that the health provider can use when assessing a patient's plan of care.

2. Role of AI in Remote Patient Monitoring

Remote patient monitoring (RPM) technologies can identify worsening conditions earlier and more efficiently than legacy systems. However, RPM systems and sensors collect a large amount of data, and sifting through raw data to find clinically significant information is typically inefficient and inaccurate. Moreover, anomalies and changes in raw data with clinical significance are often difficult to detect using statistical methods alone, because routine activities and care plan deviations can affect the rates of change of physiological measures as much as the direction. As a result, RPM systems may produce hundreds of wasteful and anxiety-provoking alarms per day. AI technologies, including machine learning algorithms and predictive models, can greatly increase the utility of RPM systems. First, AI technologies can analyze the collected data and generate alerts and insights of specific importance to healthcare providers. These approaches include predictive modeling, remote identification of physiological decompensation and exacerbation, and tailoring care plans to patient phenotype. More recently, AI technologies have been proposed to aid healthcare providers with nascent telemedicine systems in determining the 'right time' for unscheduled remote evaluation by a clinician for a given patient.

With data-driven predictions, AI technologies and RPM systems can alert healthcare providers to situations that require their immediate clinical attention and emphasize the importance of having clinicians involved in all rounds of RPM alerting. AI technologies such as natural language processing can also be used to further analyze patient-generated narrative data and explicitly track fluctuations in individualized and patient-specific goals and care plans. Furthermore, tailored and actionable alerts may be delivered by RPM systems to individual patients in ways explicitly aimed at encouraging changes in behaviors, such as enhancing engagement and adherence to self-monitoring. AI incorporated into RPM systems can also modify alerts and frequencies depending on patient identification and reactions to those interventions, thus blending RPM with telemedicine. Additionally, alerts and remote triaging by RPM systems can help anticipate the potential burden on healthcare providers due to exacerbations of chronic diseases, such as attempting to reduce delays in care and alleviate expected crowds in emergency rooms during post-discharge periods.

2.1. Advantages of AI in RPM

Remote Patient Monitoring (RPM) systems have the potential to significantly enhance the ability of healthcare systems and providers to care for patients. AI can bring significant advantages to RPM systems from the stage of data collection. It can enhance the ability of a system to process large amounts of data in a significantly faster time than humans can and to do so effectively. Thus, it can work even when presented with an amount of data that is too large for humans to handle. Rapid analysis of patient data is critical for lives and is one of the key advantages of incorporating AI into RPM tools. RPMs using AI can provide real-time or near real-time analysis of a patient's data and allow healthcare providers to make rapid decisions based on this analysis. Moreover, AI can provide the advantage of prediction based on learned patterns. Beyond real-time analysis, the system is able to interpret patterns and predict what will happen in the near future. While an alert when a patient's condition is worsening can be useful, an even better solution is to inform the healthcare provider(s) before the problem escalates, promoting early and effective intervention. Predictive analytics can be used to gather data not only from the healthcare records of each patient but also from the experiences associated with similar patients. This can be used to create a longer-term view of an individual patient in the context of others and understand what to anticipate from this patient. Such prediction allows for a predictive healthcare model, where the emphasis is on improving population health and delivering care management to those who are at higher risk, those who will have a higher cost in the near future, or those who may have the worst health outcomes. Overall, the integration of an AI-driven RPM with other healthcare technologies can be used to create a tool with the ability to interpret and learn from its own data and deliver more complete and comprehensive analysis to aid both healthcare providers and patients.

2.2. Types of AI Models Used in RPM

Employing AI in RPM entails employing different types of models, which are characterized by their capacity to dynamically learn and improve with new input. On a high level, these models can be broadly classified into the following types:

Supervised Learning: This is one of the most commonly used AI methods suitable for RPM. In supervised learning, the system is trained on input and output pairs so that it can learn patterns that map inputs to desired outputs. After the model is trained, it can produce the outputs for new inputs for which the desired outputs are unknown. The primary application of supervised learning in RPM is predictive analytics. Given a set of inputs and desired outputs, one trains a model to use the input data to predict the desired outputs.

Unsupervised Learning: In unsupervised learning, the system is provided with unlabeled data and learns patterns of the data on its own. Instead of dealing with labeled data sets, unsupervised learning algorithms typically examine data about patient behaviors, classifying patients into different risk categories to discover actionable information and offer better health management advice. It can potentially assist in learning about changes in overall patient health by tracking activity patterns and changes over time.

Learner-Centric: With an eye toward tailoring medical apps to individual patient needs, this application of AI and machine learning offers the potential for direct, personalized patient care. The approach presents a new type of AI ecosystem whose users might not have technical expertise in the medical or data analytics fields. Using this system, the user would teach the system by inputting state medical board-approved patient information as a "first step." The system will then take that information and search through a database of millions of other de-identified patient encounters to offer accurate prognostics. The researcher is eager to move the technology forward.

3. Tracking Vital Signs Using Machine Learning

Vital signs refer to basic physiological parameters that are important indicators of a patient's health status. These include heart rate, blood pressure, respiratory rate, and body temperature. Other physiological indicators may alternatively be used as vital signs in certain circumstances. Timely and accurate measurement and tracking of these vital signs are crucial both for inpatient care and in the context of remote patient monitoring. While traditional ways of monitoring vital signs, such as physical examinations and manual measurements by healthcare providers, are widely used, they may not be timely due to the large number of patients served by a limited staff. Furthermore, these methods may not always be accurate or standardized. Efforts in developing systems and technologies for automatically tracking vital signs have thus been driven by these challenges.

With advancements in digital wearable technology, wearable devices have been developed that can continuously track and monitor patients' vital signs outside of hospitals. Many of these use wireless data transmission to support remote patient monitoring. Nevertheless, to incorporate remote patient monitoring results in the timely care of patients, wearable devices need to be able to continuously track patients' vital signs and alert healthcare providers in a timely manner when a patient's vital signs are deteriorating. Machine learning, with its ability to analyze real-time data in conjunction with historical measures, is ideal for this scenario. Machine learning enables these intelligent embedded systems to detect anomalies and either autonomously act upon them or send alerts to healthcare providers in a much more proactive fashion than traditional systems are capable of. The potential of these intelligent systems to enable improved patient outcomes is, therefore, readily apparent.

3.1. Overview of Vital Signs

Vital signs are commonly utilized in patient care to offer initial clues to a patient's overall state of health or disease extent. Although multiple other assessments are expedited by EHR integration, tracking vital signs identifies any overt alterations across the dimensions of the patient's general physiology. There are four standard vital signs: temperature, pulse, respiration, and blood pressure. These signs provide valuable information about an individual's well-being and their capacity to sustain activity in the ambulance. These are continuously monitored by the ALS crew en route to the hospital to assess how a patient is compensating and therefore acting more closely if need be.

In a traditional setting, vital signs are acquired through various forms of equipment that constantly measure or intermittently assess body functions as a gauge of overall health. These body functions and their fluctuations shed light on homeostatic regulatory capacities. During an emergency, the basic purpose of assessing vital signs is to determine the mechanistic significance of the variability in the measured values of vital signs. A hard and fast rule for normal values for vital signs rarely is applicable for every individual. The variability among humans in the dictated acceptable range of heart rate, respiratory rate, and blood pressure can vary with the level of fitness. Continuous changes in vital signs display the dynamics of physiological changes in this individual patient. These shifts need to be monitored so that they do not reach crisis levels.

Variations acutely in temperature, pulse, respiration, or oxygen saturation could lead to sliding toward an urgent health crisis.

3.2. Common ML Techniques for Vital Sign Tracking

3.2. Tracking Vital Signs. Recent ML techniques offer differentiated capabilities in automatic tracking of vital signs and health conditions. The most common ML algorithms are as follows: Decision trees and random forests can handle tabular data and predict outcomes. Their structures are suitable for the modeling of tabular data, such as continuous or discrete variables. These algorithms have been used for vital sign modeling for health care data as predictive models. Support vector machines are models that can be used to perform classification. They can function as binary classifiers and solve linear and non-linear problems. Because of the effectiveness and flexibility of SVM, it can be used for large classification problems related to vital signs. Neural networks for function regression can predict an outcome using health data. They can be used as an end-to-end model to classify and predict outcomes based on continuous or discrete data. Neural networks have the ability to model the data efficiently and are used to improve the capacity of a model for real-time processing of health conditions. Supervised learning is one of the most useful ML techniques for processing vital signs. This technique focuses on the creation of models using examples that include input-output patterns stored in the dataset. Supervised learning can model and predict the health patterns obtained from processing intelligent health datasets. Neural networks can be expanded for classification as well as function regression. Convolutional Neural Networks are widely employed for remote clinical monitoring technologies using different types of health data.

Feature engineering is done after collecting the data to develop the vital sign behavior for the ML model. It further improves the learning algorithm by using the combination of extracted features that show the best results of the output values. For remote clinical monitoring, feature engineering helps in the health data characteristics, low-level, mid-level, and high-level feature creation for intelligent monitoring. ML techniques facilitate monitoring over vital signs despite the variability and noise in real data and have advancements for different types of diseases present in health conditions. When employing an ML model for remote patient health condition prediction, it is critical to consider the effectiveness of the model to safeguard health conditions. An extended version of the ML model improves the outcomes of vital sign data and these techniques can be adapted for use in the proposed solutions.

4. Health Metrics Monitoring with AI

Signifying a patient's state and understanding the associated implications are two key dimensions of health intelligence in remote patient monitoring. In this context, in vivo health metrics measurement represents one of the most straightforward metrics to monitor. Body weight, glucose, acetone, and cholesterol are a few compounds for which technologically feasible systems are available as components of a patient's health status. Different physical activity trackers offer additional insights into a person's overall observed physical activity. Perturbations in such metrics have been shown to offer initial signs of an abnormal health state and eventually unhealthy small molecules summary endotypes at a higher level. Health metrics are fundamentally different from molecular profiling based on deep endotypes due to the molecular biology observations summarized above. More importantly, the activation of the immune system has a profound impact on health metrics.

Monitoring such health metrics can facilitate the chance of earlier intervention where more time-constrained and likely life-saving alternatives exist or are more attainable due to low cost. The great value proposition of an RPM system is that with timely interventions derived from in vivo health tracking, as well as the incorporation of lifestyle and environmental data into the models, health metrics could further improve patients' chances of survival. Past work successfully leveraged in vivo health metrics for RPM in a variety of settings featuring a variety of AI and digital health metrics sensing technologies. In this review, we offer case studies that are demonstrative of different technologies and realize different use cases as a concrete manifestation of numerous opportunities based on the mechanistic basis of disease biology.

4.1. Types of Health Metrics

Remote Patient Monitoring (RPM) aims to establish insights into human health by observing routine behaviors and measuring essential health metrics via wearable, ingestible, or external devices. Essential health metrics can be classified based on their origin and are crucial in determining the health and well-being of an individual. Clinical Metrics: These are the objective metrics managed by medical professionals. They include heart rate, body temperature, blood pressure, laboratory results, X-ray or MRI reports, and so on. These metrics provide a clinical indication of the patient's deteriorating health and are used to assess the next steps in the treatment procedure. Lifestyle Metrics: These metrics involve the physical activity index of a patient, community interaction, nutrition intake, water intake, exposure to the sun, manual treatments, sleeping index, pharmaceuticals, and functional index. Apart from this, there are certain patient-reported outcomes that provide feedback from the patient, such as fatigue, pain, cognitive functions, respiratory disorders, and so on. This information is usually qualitative and is obtained through questionnaire responses. Intermixing/Correlation of the Metrics: AI-correlated prognosis for informed prediction is essential and is often overlooked by RPM systems that rely heavily on clinical data, ignoring qualitative information. As a result, several AI models were developed with clinical lifestyle intermix utilized for effective simulations.

4.2. AI Applications in Health Metrics Monitoring

This paper is framed in a style of paper using LaTeX's aastex format for Machine Learning for Healthcare and Life Sciences. We follow the format, file structure, internal structure, section header, and detailed components provided by Instructions for Authors. 1. Topic: Driven by the current situation, the COVID-19 pandemic, the world emphasizes disease prevention and remote patient monitoring, resulting in great potential and market space for relevant AI systems. This paper introduces related technologies and products in the fields of AI and RPM. 2. Summary: Tracking health-related metrics can flag trends that evolve into serious disease. Of course, this has been going on for decades. What's new is AI systems, machines that learn from the data without programming and are available to analyze remote patient RPM data collected from smartphones, wearables, and medical devices, filling the gap between drug treatment, hospitalization, and office diagnostic testing. These AI systems can handle different types of data and analyze data millions of times per second, often providing real-time signals that can help doctors predict potential crises and take action. Some systems provide doctors with algorithms that understand patterns from many patients who have the same problems to help them make decisions about drugs and care. Others analyze data for individual patients and create general patient profiles that are adapted to the individual's daily profile for alerts and responses. Abstract: Artificial Intelligence and machine learning are demonstrating growing applications in our battle against the COVID-19 pandemic and lifestyle diseases. Through AI, smart algorithms can know about you even better than you do. Do you want a new way to manage your health? There is a boom in the field of AI diagnostics that are working to improve the software that collects and analyzes data continuously for slight shifts in individual patterns that are often the first signal of underlying health changes. A prolonged onset of illness can read as increased heart rate, blood pressure, and irregular heart rate patterns. A trend of movement quantified by walking speed and instability can provide extra data to geometrically suggest a step change occurred in the vital signs, suggesting a downstream illness evolution.

5. AI Approaches for Patient Behavior Analysis

Patient behavior analysis is important for Remote Patient Monitoring. Understanding patient behavior, linking behavior and health, and using the right data and tools to create insights that can motivate the patient to change behavior are key aspects. The analysis of patient behavior is usually used to predict future activities, events, and states. These models can show when patients may adhere to therapy, perform a follow-up activity, or respond. AI models today are able to process large sets of data and may apply numerous data features to identify and predict behaviors. These models could be further developed in the future to combine a wide set of data sources and features and perform more accurate behavior predictions.

Patient behavior is complex and is determined by multiple variables. Behavior is influenced by psychological determinants, social determinants, and environmental determinants. AI has met with a fair amount of success in this domain as well. Predictive modeling can be used to predict the next steps and operations of patients. Machine learning models have been used to classify transitions from one health state to another. These include classifying readmission within thirty days, predicting future healthcare alerts, predicting transitions in care, classifying the timing of death, and predicting someone to be a high-cost patient, labeling a patient as a high-risk progressor, and classifying other clinically meaningful transitions in care. Sentiment analysis may be used to determine patient mood, behavior, and the person’s emotional state. Modeling behavior changes and behavior patterns could help healthcare professionals better analyze the data generated in monitoring systems and provide the best possible intervention. This will move healthcare systems from simple data collection to big data analysis and personal insight. Patterns in behavior can be used to design and stratify care based on the needs of patients and develop the best custom care plan. The analysis of behavior patterns and models based on them shows good results in improved patient adherence and engagement. There is a cost impact on the release of the model that shows an impact on patient outcomes. Long-term release needs ongoing RCTs to prove long-term outcomes. This is driving technological advancement in the RPM world regarding the ability to monitor and analyze patient behavior to improve patient adherence, build custom patient pathways, and manage patient behavior medications in line with care plans. Identifying the root causes of non-adherence to behavior change highlights the importance of learning how to improve adherence and technological effectiveness in interventional outcomes. Research must be conducted to take this model into parts not previously researched.

5.1. Importance of Patient Behavior Analysis

A widely acknowledged statement in healthcare is that 50% of patients do not follow the agreed treatment. A treatment may be as good as the most effective evidence shows, but it is 100% effective if the patient fully takes part in it. New, more effective drugs become less effective with low adherence levels; new diagnostic tools become less effective with delayed introductions, and lifesaving therapy monitoring may be crucial in identifying non-responsive patients. Not only disease, but also the socioeconomic context and the behaviors triggered by the mental health of individuals and their families may seriously affect the final outcome. Trust, the level of information about a specific medical disease, socioeconomic barriers, health systems, and contextual variables such as peace, education, and poverty, among others, play crucial roles in triggering specific behaviors and clinical decisions. Thus, patient behavior is an individual response to complex biological, psychosocial, and environmental interactions, as well as contextual and commercial variables. In the case of RPM, behaviors to be assessed are those able to potentially impact patient care or those aimed at the provision of care. Information about feelings, beliefs, knowledge, and processes associated with performing a particular health-related behavior and associated patient outcomes are individual behavioral determinants essentially reflecting the characteristics of an individual patient assessed over time. Measuring patient behavior can support a better understanding of which patients are non-adherent and which patients perform specific health-related behaviors. It can support tailored patient intervention, besides providing a more accurate type and frequency of consultation companions. A real-time patient behavior feedback system allows for detecting very early stages of changing patient behavior, thus helping the prevention of health loss. Such systems in health can ensure a timelier diagnosis, critical for improving disease prognosis, providing early clinical data evidencing patient need for attention, needing intervention, or other diagnostics to exclude specific diseases. If the system delivers those learnings in a specific timeframe, it is not only relevant as a diagnostic tool but also in quantifying future healthcare costs related to the designed care pathway.

5.2. Machine Learning Techniques for Behavior Tracking

Unlike supervised learning, which focuses on predicting a dependent variable based on provided input data, this type of machine learning focuses on understanding patient actions and taking actions that lead to desirable outcomes. This kind of understanding is key in RPMS, as it can provide insights to prevent patient deterioration before it happens or to tailor an intervention for patients. Clustering is used to uncover patterns in the behavior of a patient after data collection. A key aspect of clustering is that it proceeds in an unsupervised manner so that trends that are not apparent can be discovered. Decision trees can be used to uncover trends between different patient attributes. For example, doctors can identify patients who are at low risk of taking up an intervention based on the actions they do not have. This can then guide decision-making and tailor the intervention for the remaining patients. Reinforcement learning is used for behavior tracking, where the patient's actions influence which future observations are made about them. A key aspect of reinforcement learning systems is that they provide real-time adaptive intervention. Rather than aiming to uncover a well-performing treatment, the focus here is on quickly guiding the intervention to the most appropriate alternatives while minimizing the cost of any initial decisions. This technique has many far-reaching applications in medicine, but using this type of system requires addressing many challenges, most notably around data privacy.

For RPMS in particular, behavioral information is currently mainly collected through purely or hybrid medication adherence monitoring systems, while there is potential to gather a wider range of patient behaviors from all modalities. Face-to-face consults gather a wide range of behavioral information, but there are emerging technologies that could be used to monitor patients' behavior and provide more detailed information at smaller time intervals. An example is an appointment booking consent app, which can provide information about patients' decision-making around treatment. Care must be taken when deploying these more invasive systems, and one must ensure that all patients are comfortable having video consultations if they want to interpret consumption from video data, because the use of video data may disproportionately impact some groups. Machine learning opens the door to a variety of techniques that can provide insights and make predictions about patient behaviors. Although this systematic review focuses on statistical methods, it begins with a discussion of the state of the art in the field and hints at the fact that adaptive online systems may be able to use patient behavior tracking to carry out real-world interventions. A real-time adaptive intervention system for a particular subgroup of patients suffering from depression and attempting to recover from a heart attack used both clustering techniques to identify subgroups of patient behavior and then used an intervention modeling approach. It was found that the heterogeneous responses to positive thinking exercises were due to an initial tendency to engage in thought suppression.

6. Future Direction

With the ongoing advances in the development of AI technologies, we expect RPM to encompass more patient-relevant variables and to shift from a physician-driven event monitoring paradigm to a chronic and continuous healthcare model. The integration of next-generation IoT devices with wearable health technologies, in particular, will provide the ingredients on which the next-generation RPM models are built. However, while incorporating novel technologies with RPM opens up many opportunities spanning a wide range of industries, these technologies should be interoperable and open to produce comprehensive systems. This, in turn, requires that the shadow of the internet and technology conglomerates monopolizing various points of the health value chain be prevented by means of regulation.

RPM systems will be able to provide unique insights into the health of individual patients and subpopulations. Current RPM systems mainly focus on clinical parameters, but the integration of consumer behavioral data can also enhance the construction of more accurate predictive models. There are also many ethical implications that need to be addressed around the use of AI in this context, such as ensuring that patient data privacy is adhered to and that algorithm decision-making is transparent. Particular attention to AI 'fail modes' is crucial to ensure responsible AI and can lead to societal acceptance of the technology. Finally, regulation will shape the landscape of the clinical use of AI in RPM. Hence, adaptation to these changes needs to be proactive in the clinical and regulatory environments.

7. Conclusion

Machine learning models for RPM are showing impressive results in practice. Despite various challenges that face contemporary RPM, researchers continue to develop and test machine learning models. The need for informatics in health and telemedicine and RPM particularly is not lost on system architects and designers. Implementing these systems correctly contributes to the increase of patients that can be served, and patients can lead happier and healthier lives. Today's computing power enables health providers to gather a wealth of information on vital signs and patient behaviors. It also allows continuous monitoring of patients with chronic conditions. The key is to progress in collaboration, develop patient-oriented, and machine learning models based on the health metrics and the big Vital Signs data. Remote Patient Monitoring (RPM) has the potential to revolutionize the way in which patient health is managed. RPM is just beginning to realize its potential, especially in low-resourced health systems. Integrating AI in RPM supports and will continue to transform the health care system today. The patient, knowledgeable in their health behavior, can use RPM to enhance their practice with patient education, health management, and self-empowerment. The analysis and monitoring of health metrics, the patient's vital signs, and patient behavior could result in considerably improved care. The theoretical foundation in health analysis is integrated and richer when considering patient metrics holistically. It provides a myriad of factors to consider customizing and personalizing patient treatment plans, patient management, and health policies. As RPM progresses, there is potential within RPM as well as the remote leveraging of Didactics and knowledge in the services of health care personnel to address healthcare provider shortages and improve patient management overall. Additional key questions that need to be asked are: Just what ‘is’ remote patient monitoring (RPM)? In its typical use case function, does it follow all of the components that must go into modern healthcare service delivery? A possible RPM scenario by quickly and simply relevant components of an RPM service. Many devices and instruments that could be used to harness RPM’s complete abilities are not considered in this assessment and would need to be further investigated. Also, RPM has the potential to monitor patient biological systems, patient adherence statistics, patient health behaviors, and/or patients' treatment plans. In addition, many patients are being monitored by practitioners for mental and emotional or social disorders. In many or most instances, the results and RPM connections that professionals use to be able to monitor and assess general human health are not typically stored and accessed as a combined pack of information assets that could be used together, for a deeper RPM look into all service opportunities. And more than likely, they are not used in the average RPM service plan, largely because integrating all of them has not been considered and the potential usefulness and RPM service power-boost from them is not yet widely realized in the daily health service scenario landscape. As such, the main incremental challenge to RPM today's service practices is primarily a major limitation of the RPM system perspective. Online and in-person in-patient clinical strategic consultation, health treatments, prescriptions, rehabilitation exercises, and many types of training are common today with necessary skills, and strategies are needed. If such RPM services were created and integrated into an available medical service delivery process, with both of them informing each other completely, for one and all, there is great potential for improvements in all services.