Continuous Physiological Signal Analysis and Clinical Alert Generation: Real-Time Machine Learning Systems for Chronic Disease Monitoring and Management

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1. Introduction

The incorporation of technology into healthcare is predicted to significantly improve patient outcomes, improve overall patient care, assist healthcare professionals in making clinical decisions, and enable the rapid diagnosis and management of a range of health conditions. An area of growing interest in healthcare is real-time systems as part of the Internet of Things. Chronic diseases such as diabetes, COPD, cardiovascular disease, and various mental health conditions are now among the most prevalent health burdens of the 21st century. Consequently, there is a need to monitor and manage chronic conditions, encourage and monitor medication adherence, and use smart systems to help patients be more engaged in the management of their conditions. These real-time AI-powered systems allow continuous health management and have great potential for big data analytics.

An AI-powered clinical decision support system is a clinical decision support system that uses AI techniques to assist healthcare professionals in making clinical decisions and its primary purpose is to improve clinical practice. Big data analytics is identified as the capability of distilling insights from a wide array of data types, typically with new and novel processes. In the healthcare context, big data refers to electronic health records, socioeconomic information, emergency department records, clinical management data, and biometric monitoring feeds. Also called digital biomarkers, continuous patient health data can be invaluable, allowing for analytics, real-time tracking, and personalized healthcare. The use of apps, wearables, implants, and the like that monitor a patient usually signals the creation of big data. Laboratories, hospitals, and other physical data sources are used for data analytics. In addition, literature data, specialist medical opinion with genetic data, blood tests, biometric information, images, and data from electronic health records are a further facet of the compilable big data set in healthcare. Decisions based on research evidence and individual patient care delivery are the two areas influenced by big data in healthcare. Conversely, big data analysis can identify areas for improvement in healthcare and allow large study data for pattern recognition, for direct benefit in the improvement of the patient pathway.

1.1. Background and Significance

1.1 Background and Significance Chronic Condition Management: Not long ago, chronic disease management was slow-paced and labor-intensive, accounting for fewer targets and featuring largely one-size-fits-all interventions. In the last 2-3 decades, we have seen a major advance in technology to support diagnosis and monitoring, alongside substantial changes to the care landscape. These advances have enabled a much richer evidence base to support patient management that can be delivered in the context of multidisciplinary care. However, care plans have remained largely fixed, and general recipes have been replaced with targeted interventions, both of which are supported by patient self-management interventions.

The Changing Landscape: Chronic diseases are predicted to account for almost three-quarters of all deaths worldwide, with a significant portion of people having at least one chronic condition. In more wealthy countries, healthcare systems are struggling under the increasing burden of patients seeking care, with all complexities of care at organizational, professional, and patient levels. These figures are incredibly stark and have prompted a new buy-in and political manifesto for self-management, or what some call people-powered health. Reports have highlighted the need and solutions to stratify patients according to capability, motivation to adopt, or need help in planning, managing, and delivering self-care. Some have suggested that the challenge lay in proactively influencing a patient's capability and, more importantly, their motivation to adhere to medication and supportive interventions. Incremental steps in this direction.

1.2. Purpose and Scope

AI-Powered Systems for Patients with Chronic Conditions Adherence and Outcomes; Purpose and Scope

Given the gaps in the literature identifying AI-powered, real-time systems built with the patients in mind that share data with health professionals, the purpose of the research proposed here is to design, build, and test an AI-powered real-time system that can be applied specifically to patient management for chronic diseases, with a focus on patient adherence as well as tracking patient outcomes. The overarching goals of such a system are to improve patient adherence and, in turn, maximize successful patient outcomes in the context of managing chronic diseases. Furthermore, the goal is to incentivize the provision of such a system to patients as part of treatment.

This research will focus on how AI technologies can be used to enhance keeping track of patient adherence as well as feeding back to patients how they are doing compared to their peers. We will explore AI, gamification, responsive video and chat interfaces, and different user device front-end interfaces. In this paper, we will report on the work done on gamification and the use of responsive, real-time video. The focus of the paper will be on sharing how these technologies can be used for real-time monitoring of this important burdensome symptom and, critically, encouraging adherence to treatment. The intended audience for the proposed research project is healthcare professionals and commissioners responsible for commissioning services and tools for patients in the above condition area. As such, the input of healthcare professionals will be vital from the outset so that the proposed research serves the proposed stakeholders' needs. The provision of patient-consented data will be overseen by the patient-led steering group.

Significant expertise in digital engagement tools has been developed, including tools with a responsive interface to match real-time patient data with standard video answers. A tool developed to link air pollution data to health data has resulted in the formation of a spin-out. Furthermore, expertise has been obtained in using gamification to engage people in educational and reality-based game models. A solution is typically found at this boundary between different stakeholders – both of whom have different needs and cannot see themselves coming together to create a solution.

2. Chronic Conditions and Patient Adherence

A chronic condition is an illness that persists for an extended period of time, typically more than a year, requires ongoing medical attention, occasionally limits one's day-to-day operations, and frequently necessitates a long-term care plan. More than half of the global population has one chronic disease, with millions struggling with more than one. Chronic diseases like diabetes, hypertension, depression, and asthma are among the most common diseases. Furthermore, these ailments have a negative impact on a person's way of life and necessitate lifestyle alterations. More than 50% of chronic disease management protocols are given with recommendations for medicine. Because of possible toxicity, prolonged dependence, denial, and the stigma of being seen as "sick," individuals are often hesitant to take drugs at first.

Adherence is determined by the following factors: patient-related, social, economic, health system, condition-related, treatment-related, and healthcare professional team. Psychological factors seem to have the most impact on adherence to non-pharmacological interventions. There is a robust link between adherence and management of the condition. A 10% to 60% non-adherence in disease management is documented. Rates vary from 11% for the management of patients with arthritis to 93% for the management of patients with dementia. A gap is evident in the literature on the frequency of adherence and factors in disease management. When the elements in the context of chronic disease management become clear, medication will fail if compliance is not enhanced. The purpose of this study is to use technology to help individuals deal more effectively with their long-term disease.

2.1. Overview of Chronic Conditions

Chronic conditions such as ischemic heart disease, diabetes, and chronic obstructive pulmonary disease (COPD) can be classified as long-term or recurring conditions requiring continuous medical care and long-term effect management. These conditions can sometimes have a slow onset and progression and may be asymptomatic for a considerable length of time. There are five overarching types of chronic conditions: (1) behavioral health conditions; (2) cancer; (3) diabetes; (4) heart disease and stroke; and (5) respiratory diseases including asthma, chronic bronchitis, and COPD. They often result from a combination of genetics, early life events, or environmental insults such as poor diet, smoke, or infections acting over many years. Pathophysiological changes accompanying chronic condition onset and progression often result in organ damage and comorbid conditions that significantly impact the functional capacity and mental health of individuals. The evolving nature of these diseases means that management is achieved with the help of many specialists in large multidisciplinary care teams, with a mixture of diagnostics, medications, and lifestyle and behavioral changes being used to extend and increase the quality of life.

Chronic conditions impose a physical, mental, and socioeconomic burden on a patient and their family, result in increased healthcare costs, and more sick days at work or unemployment for the patient. These conditions can also lead to hospital admissions or visits to the emergency departments if the symptoms are not controlled appropriately over time. Chronic diseases represented a significant portion of healthcare spending on adults. Examples include heart disease, diabetes, and high blood pressure accounting for a notable percentage of GDP expenditure. To control chronic diseases and give access to ongoing care for the affected individuals, the comprehensive use of chronic disease management programs should be effective and, in the long term, cost-effective. Approximately 41% of deaths annually are linked to behavioral and lifestyle choices such as poor diet, physical activity, excessive alcohol consumption, and smoking. Decreasing these risk factors is crucial in preventing, controlling, and managing chronic conditions so that the affected individuals have the opportunity for a good quality of life. In addition to lifestyle factors, in terms of functional capacity, vomiting is one of the most common symptoms of chronic disease. Overall, for most individuals diagnosed with a chronic condition, it marks the beginning of increased medical costs, long-term medication, changes in functional ability, and an altered quality of life. As such, adherence to the aforementioned treatments and health maintenance behaviors, alongside appropriate screening and periodic health checks, is critical.

While the core aim of a clinician is to treat disease in its acute form and not help with ongoing chronic symptoms, these symptoms will impact the patient's quality of life and should, therefore, not be ignored. The unpredictable nature of chronic conditions and ambivalence to linked lifestyle change further complicates ongoing management of these diseases. As such, ongoing research and innovation are sorely needed to address this growing problem in healthcare. Rehabilitation is a key strategy in the management of chronic diseases, enabling patients to live life to the fullest. However, exercise-based rehabilitation programs remain underutilized. Chronic conditions such as ischemic heart disease, diabetes, and chronic obstructive pulmonary disease (COPD) are among the leading causes of morbidity and mortality worldwide and are the leading cause of death in the US. Similarly, chronic diseases such as ischemic heart disease and stroke were among the most costly chronic conditions. These costs include both direct medical expenses and indirect expenses due to lost productivity.

2.2. Importance of Patient Adherence

Patient adherence is a critical element of effectively managing most chronic conditions or diseases. Adherence is the act of choosing to do what has been prescribed for the host of conditions, to obtain the end result. Adherence is imperative to potential health resolution, while non-adherence often produces failure in therapy. Numerous studies reviewed adherence across several diseases, correlating the level of medication adherence with an improvement in clinical indices. Indeed, it is consistently revealed that improvements in adherence rates correlate with both clinical outcomes and resolution. For example, patients with human immunodeficiency virus who took over 90% of their medication doses over a three-month period had significantly higher CD4+ T lymphocyte count changes and significantly lower rates of progression to acquired immune deficiency syndrome or death than those who took between 80% to 90%, 70% to 80%, 60% to 70%, or less than 60% of their doses. In numerous conditions ranging from asthma to heart failure to mental illnesses, non-adherence poses potential mortality. Micro or macrovascular complications due to diabetes pose the most deadly complications from non-adherence results.

Non-adherence consumes many healthcare dollars and could also be measured in terms of increased rates of physician visits and hospitalization, worsening patient outcomes, increasing morbidity, and overall decreased health status. However, most healthcare providers do not wholly appreciate the massive hardships faced by patients as well as their families in implementing recommended healthcare treatment plans. They, therefore, need to be educated on support systems for people with chronic diseases. However, there are many other barriers to adherence. They can be grouped into: patient factors; social and economic factors; disease-related factors; therapy-related factors; and other related factors. Research, however, has begun to identify these factors, as well as strategies for addressing them, in a range of illnesses and older patient populations. Adherence can also be improved by reorientation of healthcare systems and the organization of care. This might include information systems to remind physicians of patient monitoring needs and other recommendations, and may even include patient management systems that can trigger patient letter reminders or enable timely follow-up by physicians. Therefore, developing information systems that enable clinicians to monitor adherence and patient outcomes more effectively may provide providers with a solution to the problems of adherence to therapy in chronic care.

3. AI-Powered Systems in Healthcare

Introduction

AI-powered systems and their potential have revolutionized multiple domains in the recent past, and healthcare appears to be the next best and biggest challenge for AI enthusiasts. In chronic care management, AI-powered systems may offer new ways to track patient adherence to protocols, flag adherence issues before the patient is off track, and, in general, leverage AI-based predictive models for flagging patients and care managers when the patient's condition may be trending in a bad direction. There are a few case studies that have successfully entwined the sensors, algorithms, and patient feedback with an emphasis on research. Patients and clinicians use AI-powered systems to gain better insights to make choices that result in better health outcomes. The AI accomplishes this by tracking information and then identifying patterns and deviations that are associated with some types of clinical decisions and health outcomes.

When AI is added to patient care regimens or patient decision-making, patient outcomes improve. There are several distinct types of AI that are used. In general, consumers and patients are much more comfortable with AI that is powered by machine learning than if the AI can explain how it came to its recommendation. The latter is a growing area of study, and it is not always well accepted. Several forms of AI technology are used in healthcare. They include machine learning, optimizing algorithms, natural language processing, computer vision, and robotics. There are several important community standards addressing the ethical implications of using these technologies in healthcare, and professional organizations have adopted ethical principles establishing a right to assisted decision-making and help. AI and machine learning, more generally, are seen as AI that can do something for the average person that a human care team could do.

There is a growing emphasis on AI that can help tailor diabetes self-management to individual patients by either tailoring or optimizing the behavior and interventions to that patient. This also means that AI does not just address people who are similar but can also suggest individual therapy based on the entire internet of data. By using real-world data, healthcare can begin to capitalize on the heterogeneous response to treatment and inform decision-making in real-time for patients who are or are not getting the anticipated outcomes or side effects. Ethical implications of using such data to make clinical decisions are an active area of discourse.

3.1. Applications in Monitoring and Managing Chronic Conditions

Real-time AI-based systems can be used to monitor and manage chronic conditions, with the ability to collect, monitor, and analyze relevant patient data in many cases. The AI tools can be leveraged to identify health issues and adjust therapies or provide recommendations in real time, leading to proactive care that can improve outcomes. Mobile applications and wearable devices are typically the primary tools for collecting relevant data, monitoring patient adherence to drug regimens, encouraging patient-reported outcomes, and providing interventions such as educational or behavioral advice. There are now apps and devices that can monitor the vital signs and blood glucose levels of patients along with the delivery of insulin or other medications and send this information to patients' smartphones, provided they wear the device. Some of these monitoring systems even include predictive algorithms that can identify when a patient may be hypoglycemic and titrate or stop the delivery of insulin.

This initiation of the remote monitoring of patients taking anticoagulants showed that the service could keep patients within the therapeutic target range for an estimated 68% of the time, reducing the need for hospital visits. Remote monitoring services have been demonstrated not only to provide similar health outcomes and increased patient satisfaction but also to reduce the risk of hospital visits in other chronic conditions such as cardiovascular disease, obstructive sleep apnea, and chronic obstructive pulmonary disease. In addition to improving patient outcomes and satisfaction, these remote monitoring technologies have also been shown to create a wealth of useful patient data and provide near real-time insight into patient progress, which can be leveraged for clinical investigation. Many of these services illustrated an improvement in at least one monitored area, such as reduced hospitalizations, reduced disability, reduced physician visits, or reduced health care system costs.

Some wearable or mobile-based monitoring systems empower patients to monitor themselves without any intervention from medical professionals. This is important for many patients with chronic conditions because it enables them to take control of their own health. In this section, we provide some examples of future trends and successful implementation in remotely monitored patients using a telehealth system, including chronic conditions such as diabetes and cardiovascular disease, to help realize the potential of processed data. Despite this, it is not always easy to obtain accurate and reliable data. During the pandemic, systems that monitor lung function in real time were introduced and applied to patients with chronic respiratory conditions. Researchers had to overcome several system performance challenges, such as frequent system outages, involuntary responses from patients, and hygiene-related concerns. Therefore, the use of this technology must be designed in a manner to facilitate use by both the patients and the health care personnel, while ensuring the ethical values regarding patient data privacy. In addition, health care technology may need to be evaluated against certain regulatory frameworks or standards, such as privacy-neutral/privacy-preserving AI tools or Information Governance regulations.

3.2. Key Technologies and Algorithms

The development and implementation of AI-powered systems are supported by many well-established technologies and algorithms. Nevertheless, these systems often bring to medical practice the latest innovations from fields like data analysis, network computing, and artificial intelligence. Therefore, the question of "novelty" and "innovation" in such applications is better addressed by examining the algorithm improvements rather than the involved technologies. Note that the chosen algorithm is always best adapted to address the particular challenges faced by healthcare stakeholders. Here we provide relevant information about the basic technologies and algorithms commonly used to develop AI-powered healthcare systems.

Several challenges exist in healthcare today that can promote the use of the algorithms discussed above. This includes monitoring and managing chronic conditions and monitoring the changes associated with aging. These algorithms are employed to provide features including data analytics, predictive modeling, and association rule mining to track a patient's adherence and outcomes. Several challenges exist with the further use of these algorithms based on limited sensor information and human measurements. In general, modeling patterns of this type may require the use of long-term, large datasets. The advancements in machine learning, in particular, deep learning, have made it possible to capture patterns and develop models that uncover important features in online data. Big data analytics and deep learning algorithms can provide AI models that outperform traditional models. Nonetheless, such algorithms are computationally expensive compared to conventional models, thereby catering to the need for significant computing infrastructure for real-time patient management systems.

Although a subset of sensor data has to be saved, a generic system like a smartphone is more suitable for the implementation. It is important to note that these algorithms have significant limitations regarding features based on real-life data, including large datasets. Furthermore, issues related to privacy need to be considered, and the algorithms must be developed considering the unique characteristics of the diseases for which these systems are being developed.

4. Machine Learning for Patient Adherence

One of the avenues where machine learning can significantly contribute to the management of chronic conditions is in fostering patient adherence and decreasing cases of missed or skipped medication intakes, thereby leading to more consistent data and overall better population-level analyses of effectiveness in the real-world use of prescribed drugs and therapeutics. Patient adherence to therapy is widely cited as one of the major issues in healthcare because it is low across all therapeutic areas, including but not limited to cardiovascular diseases, diabetes, and numerous chronic conditions. Poor adherence leads to poorer health outcomes when comorbidities arise and diminishes the effectiveness of clinical interventions. While there are countless strategies for how to study adherence, it is widely understood that the first and most necessary step is for any patient and provider to know whether or not medications have been taken—especially because a major factor in cases of poor adherence is an underlying issue of a lack of self-efficacy or behavior-building habit to adhere to treatments.

The previously described machine learning models approximate this often-undocumented real-world patient behavior to provide actual evidence of patient adherence to healthcare providers. Predictive models employing rarely complex machine learning algorithms can be trained on weekly data to predict who will be nonadherent to the at-home dosing procedure within confidence intervals (at the time of enrollment, before any actual dosing has occurred). In addition, treatment effect estimators can be applied to a given feature vector of plan-relevant adherence-point descriptors in order to properly target adherence-improving incentives. There are likewise machine-learned algorithms for this; one example of just such an algorithm has been demonstrated in a clinical trial as effective in fostering engagement and improving adherence behaviors via incentives. Of course, these kinds of predictive machine learning algorithms are not limited to patient adherence to treatment—for example, they have been deployed in predicting prizes rather than medications in targeted messaging to increase college student adherence to yearly flu vaccinations. Since chronic condition management is a burgeoning public health concern, and conditions likely requiring long-term regimens have a much higher nonadherence rate than short-term regimens, optimizing for patient adherence is of paramount concern. As such, these kinds of engagement-based incentive systems are especially of interest to healthcare clinicians, given that both engagement and adherence are key markers in clinical decision-making in individual patient care. The aforementioned example of the machine-learned adherence-incentive model for improving national vaccination coverage has, for example, improved patient motivational adherence markers. In this example, across approximately 20,000 college freshmen assessed across two studies, patient (student) reported adherence increased across a variety of self-report metrics (including a Likert rating of conviction to obtain a flu vaccine, flu vaccine behavior measured as an odds ratio, and self-report my shot score). Following the effect of incentives and algorithmic reinforcement of motivational strategies, patient-motivational growth markers were tracked. Barrier: Dissemination of Interventions Barrier: Motivational Psychology Insights from behavioral psychology can be utilized to develop a patient-adherence algorithm set that provides a treatment strategy for each individual's unique psychological makeup (which can differ on both diagnosis and major influencing drivers of their behavioral adherence—or lack thereof). Mechanism for Treatment Increase in National Rates of Adherence Empowerment of Providers Per-Entity Personalized Information and Interactions

4.1. Role of Machine Learning in Enhancing Adherence

Enhancing Adherence. Machine learning can help predict which patients are at an increased risk of premature treatment discontinuation using data from EHR. Real-time availability of EHRs enables bi-directional interaction between machine learning agents and the patient. For example, cloud storage and wearable sensors have two key functions: real-time monitoring and disease progression in parallel with treatment response and real-time feedback to the patient and healthcare provider. The sensors, smart devices, and applications enable the patient or caregiver to monitor and interact with care, with or without disease specified or inferred from symptoms - relevant data and patient engagement data. The relevance is not necessarily to the scientific community, but to the patient and caregivers.

Developments in Machine Learning. Machine learning is used to classify patient attitudes by analyzing linguistic cues used in online comments. Another application of machine learning involves developing, optimizing, and personalizing high-level treatment strategies. This approach uses reinforcement learning to automatically optimize and adapt treatment strategy at the level of personalization of dose and timing. The discount value and the target value can be adapted to personal adherence behavior. One further approach is to develop machine learning models based on adherence data to accurately predict a patient's future adherence and proactively intervene prior to the event occurring. This approach uses prediction models with multiple data inputs to demonstrate that correct predictions of which interventions a patient is likely to respond to are better using insight on past treatment response as well as adherence. Machine learning algorithms can be used to assess a person's support network, and a social network can be integrated into the healthcare journey.

Finally, machine learning models can be used to better understand the personal barriers to treatment burden, non-adherence, and treatment outcomes by extracting relevant markers of patient behavior through the analysis of personal health-related data. From this model, differences between patient groups central to real-world treatment paradigms can be calculated, and an estimate of how patients with a defined barrier would respond to its removal can be made. Addressing the challenge of managing chronic illness associated with cognitive decline is the next frontier for AI-powered tools. Service providers also offer a range of applications based on AI and machine learning techniques. Evidence for the impact of these technologies would represent useful and practical applications for life science leaders involved in decision-making for reimbursement programs and biomedical research. Although this is an area of emerging importance, new evidence is currently limited and would be of great relevance to the initiative.

4.2. Predictive Modeling and Personalization

Personalized healthcare solutions based on a synthesis of medical data, clinical guidelines, disease progression, and predictive modeling are of the utmost importance for the management of patients with chronic conditions. Predictive models can synthesize all available data and assess individual patient information in an attempt to forecast risks of non-adherence and propose patient-specific intervention strategies.

These strategies can improve the quality and efficiency of healthcare by leading to a decrease in the costs associated with repetitive medical procedures and preventable hospitalizations and, at the same time, improve patient well-being with proactive management and patient engagement. As predictive models become increasingly accurate, healthcare providers are able to achieve reasonable engagement levels to support the growing body of evidence that shows an association between patient adherence and improved health outcomes. Through machine learning, such models can be developed, allowing for personalization as well as the continuous refinement of prediction models.

The adoption and implementation of the above-mentioned solution require the identification of the risk factors of interest, alongside information on their predictive accuracy. Different statistical techniques exist for the identification of the relationship between these factors and adherence and/or the prediction of mortality. Additionally, continuous engagement with the subject is of utmost importance in the continuous refinement of prediction models by enabling dynamic model development based on patient feedback. Real-time systems can monitor modeling performance closely and address issues or limitations as they emerge. As for ethical considerations, predictive models use patient information to derive actionable insights and could have a detrimental effect on patient welfare if the modeling assumptions and data are flawed or misaligned with the individual's health needs.

The implementation of data-driven, personalized prediction models that assess patients' levels of adherence to complex drug regimens and/or lifestyle changes is increasing. Predictive insights add a layer of personalization that accepted trials are unable to achieve, focusing on the benefit of individual patients' predictions rather than "in the average patient" (parallel care). In some instances, positive results were attributed to highly engaged patients seeking personalized and novel care options tied to their level of risk or adherence. Many industry and academic case studies have been published, with varying degrees of improvement in supporting therapy adherence or mortality prediction. More instances are also becoming available with personalized, machine learning-based models. Regulatory agencies are also recognizing predictive modeling-based real-time improvements in predictive model performance. What these instances have in common is the use of personalized prediction games based on frequent monitoring and outreach error feedback.

5. Outcome Tracking and Data Analysis

5.1. Outcome tracking, intervention success, and patient-related outcomes Patient outcomes are a feasible endpoint for evaluating interventions as more years are accumulated and problems prevented. Outcome refers to all the possible results of an intervention in a patient and may follow the expected action of the investigator or overshadow the expected effect with other complications. The leading use of any outcome is to evaluate whether an intervention is successful or not, whether it is acceptable in general, and can provide valuable information about the effects of treatment in subgroups and the potential moderators of the outcomes.

There are several methods for tracking patient outcomes. Often data are collected through self-report questionnaires, validated outcome measures, ecologically valid assessment, digital diaries, existing health data from medical records, insurance statistics, and aggregations of comorbid diseases and medications. In most settings, data are self-reported through surveys and, in clinical settings, by a range of providers including therapists, educators, enrollment staff, nurses, and, in primary care, practitioners. In addition to surveys, one can collect outcomes from existing health records or automatically through an electronic medical record and digitized billing records. Outcomes can also be measured with biometric data, including, for example, blood and other laboratory results, heart rate variability, blood pressure, and weight. The advent of technological advances has brought smart devices and wearable sensors to protect people's health. Wearable devices are known for their ability to continuously collect medical-grade biometric data, but the development of the technology has been overshadowed by concerns about its accuracy and data security. Commercial applications can be encouraged to use in-built smartphone sensors, because most users find them comfortable, less invasive, and perform well in automated screening processes. Tremendous digital technological advancements are being made. It is possible for internet-connected devices to monitor glucose levels and discuss medication dosage changes with a healthcare professional in real-time.

5.2. Noise in outcome tracking data The development of new devices to measure outcomes with greater accuracy and precision is of importance. However, the increased accuracy does not eliminate the noise, or random variability, in outcome tracking assessments, nor the chances that the computer will crash, and that the sensor will run out of battery power. Additionally, assessing an outcome with greater accuracy or over a shorter period of time may introduce unknown positive or negative effects of monitoring. Measuring vital signs and other relevant data is not in and of itself efficient or ethical, and is subject to the same consensus that research protocols and conduct must be established. Given that patients aggregate with healthcare facilities and providers that have the highest level of healthcare, improvements in these data may be difficult or impossible to teach or learn in their places. Deploying fewer professionals in underserved areas with greater need for care is not the goal of outcome tracking. As data catch more of the population, the social market for advice and health decisions evolves. Outcome tracking may expose healthcare malfeasance or fragment healthcare law and create greater demand for policy reforms or public resistance. Outcome tracking in real-time may also improve the efficiency of paid consultants, therapists, and others who outsource their coaching or human skill-building.

5.1. Importance of Outcome Tracking

Outcome tracking in the care of patients with chronic diseases is a powerful way to demonstrate to patients and other stakeholders that our medical treatments and behavior change interventions work. Close tracking of outcomes over time can also reveal areas for improvement. Systematic outcome tracking at the patient population level has the potential to improve care delivery by providing aggregate information across a population of patients, allowing for a more data-driven approach to allocating resources and identifying which factors could help indicate where system changes might lead to improved patient outcomes or decreased costs. The routine, accurate collection of data about a population of patients and whether they are meeting the desired health goals allows us to learn in real time about the effectiveness of our interventions and to be responsive to the impact of policy changes on outcomes.

Data pertaining to outcomes is increasingly relevant to patients themselves. Patients are becoming financially responsible for an increasing portion of their healthcare costs. Patients have been shown to choose providers based on the outcomes that are important to them, and they are interested in outcomes research and the value of the care in which they are investing. A robust system for tracking the outcomes of chronic care patients, built on a consensual framework of outcomes tracking that includes being respectful of patients and involving patients in outcome tracking discussions and implementation, is required. Then a not very burdensome but basic outcome can be reliably measured from patient to patient. Once that is done, the basic data can be collected once and then mined as if the data were stored in 'Outcome banks.' Built on data warehouses that segregate patient consent and then aggregate data on an underlying performance improvement outcomes database, these outcome banks can be mined for many different purposes. To date, the approach of this work has been tested by practicing set theory based on essential outcomes, testing data collection efforts based on these outcomes, and using a unique natural experimental intervention structure where patients who have agreed to outcomes tracking are randomized into different adherence interventions based on technology to measure daily behaviors. Key takeaways from this work are that payer, employer, and PCMH/Super PCMH incentives are essential for outcomes tracking at scale, that the analysis of the data collected shows a meaningful difference resulting from interventions providing real-time behavioral data, and that patients adhere to the use of technology that uploads the real-behavior data. This activity has led to a new, larger integrative study. Outcome tracking is a powerful way to drive value and to find what really works in terms of patient-clinician engagement, preventive behavior change, product efficacy, and care delivery.

5.2. Data Collection and Analysis Techniques

With large amounts of data being generated in the healthcare field, there are various means and methods of data collection. Some of the common sources of data include electronic health records, personal interviews, patient surveys, and wearable devices that monitor a patient's health around the clock. It is necessary to maintain the integrity of the data and always be aware of the accuracy with which a condition or activity can be assumed. More than one observation can be documented as a mistake, so meticulous data collection is crucial. Once the data is collected, various forms of analysis are performed to obtain a clear understanding of how a patient adheres to their treatments, and the outcomes are tracked. Descriptive and inferential statistical analyses help to make assumptions or predictions based on a set of data, whereas visualization of the data and the results yield an even clearer understanding. Data visualization may be easier for some clinicians to interpret, as most are not specialists in statistics. Visual representation of the data includes tables, line graphs, scatter plots, and pie or donut charts. The inclusion of artificial intelligence could further increase the potential for identified adherence factors and effective monitoring tools integrating different data exchange systems. These observations can provide feedback on future healthcare and policy development. There are several challenges to overcome for companies and academic institutions to fully understand the data collected from patients. Data from various data collection techniques can include personal and identifiable information that must be kept secure and in compliance with several rules and regulations. To accommodate data integration from various sources, a variety of synchronization methods are discussed, which typically involve handling missing values. All data should be discussed with the patient before the biggest limiting factor of any novel technology can be accomplished. Data collection methods have a significant and immediate impact on the effective results.

6. Conclusion

This essay demonstrates the increasing body of evidence illustrating how real-time, AI-powered systems play a crucial role in the management of chronic conditions. Specifically, this paper reviews important contributions with an interest in enhancing patient adherence and the tracking of outcomes for optimized chronic care management. Focusing on attracting evidence to guide research and programmatic work related to the deployment of real-time AI-powered systems to monitor and manage chronic conditions, respective evaluation is limited for global health or health equity. This retrospective study aimed to understand the potential benefits of such AI-enabled systems in managing chronic conditions, identify the gaps, and share insights into how these gaps could be addressed in the future. It is presented against a rapidly expanding body of literature demonstrating the transformative potential of machine learning work in healthcare with great variety in context, method, and applied approach.

In conclusion, there is a growing body of literature demonstrating the synergies between the use of AI and the potential for managing chronic disease. As we see increasing computational resources, data, and sophisticated machine learning techniques, we can unlock the potential of these mechanisms to understand complex interactions between patient characteristics, behaviors, experiences, and outcomes. There is a pressing need to develop sensitive measures of when these platforms have achieved the desired impact and reverse this in cases of problematic or unethical use. Moving forward, I advocate for two lines of research: to engage directly with studies combining machine learning outputs with generalizable findings regarding drivers of adherence and outcomes in clinical populations – contributing scenarios for how best to utilize this data as an adjunct to quality improvement activities; and to develop robust, value-sensitive, and ethical ways to evaluate the specific use of AI for medical purposes.