Remote Monitoring of Patients with Chronic Diseases: Utilizing Ai Technology

Kriti Verma[1], Ashutosh Nandi[2], Shraddha Negi[3], Devanshu kumar[4]
Department of Pharmacy, Alpine College of Management and Technology, Dehradun

***Abstract*—Artificial intelligence (AI) is an expanding domain with significant implications for the management of various chronic diseases. The principles of machine learning have been employed to develop algorithms that facilitate predictive models, assessing the risk of chronic disease onset and its associated complications. This review explores the incorporation of deep learning and reinforcement learning algorithms into remote patient monitoring systems, aiming to improve predictive accuracy, enhance decision-making processes, and provide personalized care for patients. Notably, advancements in Internet of Things technology, smart home automation, and healthcare systems have led to a shift in perspective, rendering in-person hospital visits less essential. Remote monitoring utilizes tele-monitoring devices within patients' homes, enabling the electronic transmission of clinical data to healthcare facilities. This innovative health intervention supports care in home or community settings, enhancing patients' self-management capabilities and overall satisfaction, thereby improving their quality of life. For individuals with chronic conditions, remote monitoring has been shown to increase disease-specific knowledge, prompt earlier clinical evaluations and treatments, and foster improved self-management and collaborative decision-making. Nevertheless, these advantages must be weighed against concerns regarding the potential loss of personal interaction and the increased personal responsibility associated with remote monitoring.**

***Index Terms*—AI, Chronic Diseases, Remote monitoring.**

I. INTRODUCTION

Chronic diseases are enduring medical conditions that last for a year or longer, typically necessitating continuous medical care, lifestyle modifications, and management strategies. They place a significant strain on patients, their families, and the healthcare system. Individuals suffering from chronic illnesses face a heightened risk of both mortality and morbidity, resulting in a markedly diminished quality of life when compared to the general population. [1] The financial burden of medical treatment and the reduction in job prospects can result in economic difficulties. The rising incidence of chronic illnesses worldwide poses a considerable challenge to the ability of healthcare systems to deliver adequate care.[1] Artificial Intelligence is characterized as a field within computer science focused on developing systems or methodologies that evaluate data and manage complexity across various applications.[2] It's critical to give patients the resources they need to actively and actively participate in the course and treatment of their illness.[3] By using technology to manage a patient's health remotely and provide continuous monitoring without requiring in-person hospital visits, remote patient monitoring (RPM) devices are revolutionizing the healthcare industry [4]. With the ability to continuously collect, analyse and provide patients with feedback on their health data from a distance, remote patient monitoring (RPM) devices have become an essential component of contemporary healthcare.[4]

1.TECHNOLOGIES USED IN RPM

In the management of chronic illnesses, wearable devices can be directly worn on the body as portable medical electronic equipment designed for sensing, recording, analysing, regulating, and intervening to maintain the health of the individual using the device.[5] The wearable devices use in (rpm) are: Smartwatches, ECG patches, glucometers, BP monitors. Lot and sensors like continuous monitoring and data transfer, mobile health apps, cloud platforms and data analytics, AI and machine learning integration. One of the most important uses of RPM is found in cardiology, especially in the management of CIEDs, such as pacemakers and implantable cardioverter-defibrillators (ICDs). Figure1 shows various Wearable devices. These devices play a crucial role in the care of patients suffering from cardiac arrhythmias, offering life-saving interventions by regulating heart rhythms or delivering shocks to prevent sudden cardiac death. However, the clinical management of these devices poses unique challenges, particularly in the post-implantation phase where regular monitoring is vital to ensure device functionality and patient safety [6].

[

Figure 1: wearable devices

II. CLINICAL INCOPPORATION OF RPM

RPM has proven to be of considerable clinical significance in managing chronic illnesses such as heart failure and diabetes, RPM has demonstrated its capability to improve ongoing disease management while also boosting patient involvement. At present, the management of chronic diseases entails a passive approach to treatment and an active approach to monitoring health status. The advent of various advanced technologies, including AI, blockchain, and wearable technology, has inspired innovative concepts for the real-time monitoring of chronic diseases. [5,6] The rise of wearable technology has also made health monitoring more accessible, enabling individuals to assume a more proactive role in overseeing their health, particularly in the management of chronic conditions such as diabetes and hypertension.[7] But despite its promise, the application of big data in chronic disease management presents numerous challenges. [7] Among these challenges are complex issues related to data privacy and security, compatibility with other Health IT systems, and concerns regarding algorithmic bias. Each of these issues poses a significant threat and warrants careful consideration from both healthcare practitioners and AI developers to create effective RPM systems.[8]

Data Protection and Security:

One of the most urgent challenges in the Internet of Things (IoT) concerning remote patient monitoring is the matter of data privacy and security. remote Patient Monitoring (RPM) systems produce large volumes of sensitive patient information, which is perpetually transmitted across networks. This information is extremely susceptible to cyberattacks, posing a considerable risk of breaches in patient data.[9] Furthermore, the interconnectivity of IoT devices within the healthcare sector introduces potential vulnerabilities. Each device that is connected can act as a possible entry point for cyberattacks. Should an attacker breach one device, they could potentially access the entire network, resulting in extensive data breaches. Consequently, organizations need to prioritize thorough security strategies that cover not only the devices but also the networks and systems responsible for data management. Regular security evaluations, software updates, and employee training on cybersecurity best practices are essential for sustaining a secure environment.[10]

Prejudice in Training Data:

AI models are vulnerable to the biases inherent in the training data. If the data used to develop an AI system does not accurately reflect a variety of patient populations (for example, regarding race, ethnicity, gender, or socioeconomic status), the system may produce biased predictions that disproportionately impact specific groups. For example, an AI system trained on a dataset primarily composed of information from a single demographic group may struggle to accurately identify diseases in other groups.[11] In the field of healthcare, this may imply that patients of colour or those from lower socioeconomic backgrounds do not receive equivalent standards of care or experience similar improvements due to the precision of analytical models. For example, a machine learning model developed using data from a specific age group, such as middle-aged white males, is unlikely to yield accurate results for women, people of colour, and the elderly. This could lead to incorrect diagnoses, inappropriate management, and inaccurate prognoses, resulting in disparities in healthcare management.[8]

Data Magnitude:

One more obstacle in the development of an RPM system that incorporates AI models is the volume of the dataset utilized for training and prediction. The majority of machine learning algorithms necessitate extensive datasets to create a reliable model. The dataset's size is significant, as it can impede the machine learning model's capacity to function accurately. In order to evaluate hospitalized data or outpatient data, an effective model must be trained with informative features and a substantial number of subjects (Ramos et al., 2021).[12]

III. METHOD

Selection Standard:

Initially, we focus on five primary search engines (IEEE, Springer, PubMed, Scince.Gov, and Science Direct); subsequently, we assess the relevance of selection-based RPMs to the following keywords (Clinical decision support systems, internet of things, wireless body area network, cloud computing). additionally, certain papers were omitted due to duplication. Ultimately, all literature was reviewed, resulting in a total of 52 articles. Figure 1 illustrates the selection and evaluation process. The paper emphasizes the examination of RPM literature over the past five years (i.e., from 2015 to 2019). We opted to exclude 2020 from the analysis as the study was completed prior to the conclusion of that year. Figure2 presents the keywords utilized to gather eligible articles and the compiled articles corresponding to each keyword.[13]

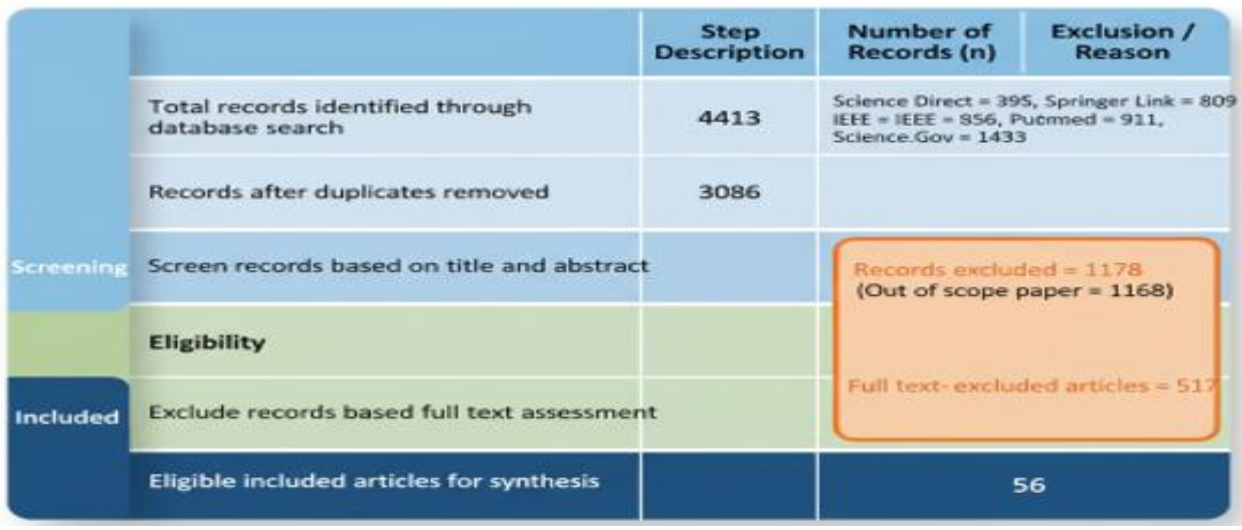

Figure 2: Article inclusion work flow

Information extraction:

Data were gathered from each of the chosen studies, encompassing details regarding the chronic disease focus, the predictive analytics techniques employed, data sources (such as electronic health records and wearable devices), outcomes assessed, and the results of the studies. This information was organized into a uniform format to facilitate consistent analysis across the studies. [7]

Analysis of Result:

The gathered data were synthesized to discern trends, common methodologies, and challenges in the utilization of predictive analytics for the management of chronic diseases. Quantitative data concerning the performance of predictive models were summarized, while qualitative insights related to implementation challenges and future directions were examined to emphasize areas of enhancement and innovation.[7] This section presents a statistical analysis of the search results from various perspectives (different domains, differences in each year). Table1 illustrates the distribution of the published articles during the period of our study (2014 to 2019). As indicated, the number of studies rapidly increases from 18% in 2014 to 33% in 2019. This reflects the growth in research related to RPMs. Table 2 depicts the distribution of the gathered articles according to the paper's application diseases. Based on these distributions, we can observe that PMs for the elderly account for the largest percentage (28%), followed by PMs for heart failure (26%). Other diseases such as cancer, diabetes, and post-surgical conditions take approximate percentage ranges from 8 to 14%.[13]

[A] Table 1: Trend analysis

Year	Rate (Value)	Change from Previous Year	Trend Analysis
2015	0.18	N/A	Baseline Year
2016	0.16	-0.02	Slight decline in rate
2017	0.15	-0.01	Lowest recorded rate
2018	0.18	$+0.03$	Return to 2015 level
2019	0.33	$+0.15$	MASSIVE SPIKE (83% increase from 2018)

[B] Table 2: Impact

Rank	Disease/Reason	Percentage (%)	Cumulative Percentage (%)	Severity/Impact
1	Elderly Diseases (Mental Diseases)	$\mathbf{28\%}$	28%	Primary Driver
2	Heart Failure	$\mathbf{26\%}$	54%	Co-Primary Driver
3	Cancer Diseases	$\mathbf{14\%}$	68%	Significant Factor
4	Movements Disabilities	$\mathbf{14\%}$	82%	Significant Factor
5	Diabetes	$\mathbf{8\%}$	90%	Secondary Factor
6	Others	$\mathbf{8\%}$	98%	Secondary Factor
7	Monitoring a Surgical Procedure	$\mathbf{1\%}$	99%	Marginal Factor

Applications of RPM in chronic Diseases:
AI-powered systems are achieving remarkable progress in the prompt identification and management of chronic illnesses, where timely intervention can substantially enhance patient outcomes and overall quality of life. [14] chronic diseases such as diabetes, hypertension, and heart failure require continuous monitoring and long-term management. Remote

patient Monitoring (RPM) provides real-time health tracking, enabling timely interventions and reducing hospital visits. It supports early detection of complications and empowers patients to take an active role in managing their conditions.

Diabetes: Diabetes is a metabolic disorder characterized by either a deficiency or resistance to insulin, a hormone that is essential for regulating blood sugar levels. Common symptoms include polyuria, polydipsia, rapid weight loss, blurred vision, and fatigue. This condition can lead to serious complications such as strokes, blindness, miscarriages, and organ failures. According to a report by the World Health Organization in 2014, around 422 million individuals globally are affected by diabetes, with an estimated 1.6 million deaths directly attributable to the disease. Medical guidelines emphasize the importance of early diagnosis to identify individuals at risk and encourage patients to actively monitor their lifestyle to reduce risk factors. Remote patient monitoring (RPM) can play a crucial role in preventing the alarming number of deaths associated with diabetes through early detection and timely alerts to both patients and healthcare providers. Figure3 helps to understand automated insulin delivery system. RPM minimizes the necessity for frequent checkups, assesses the ongoing effectiveness of treatments, and facilitates intervention strategies for notifying professionals, thus improving the overall quality of life for patients [15].

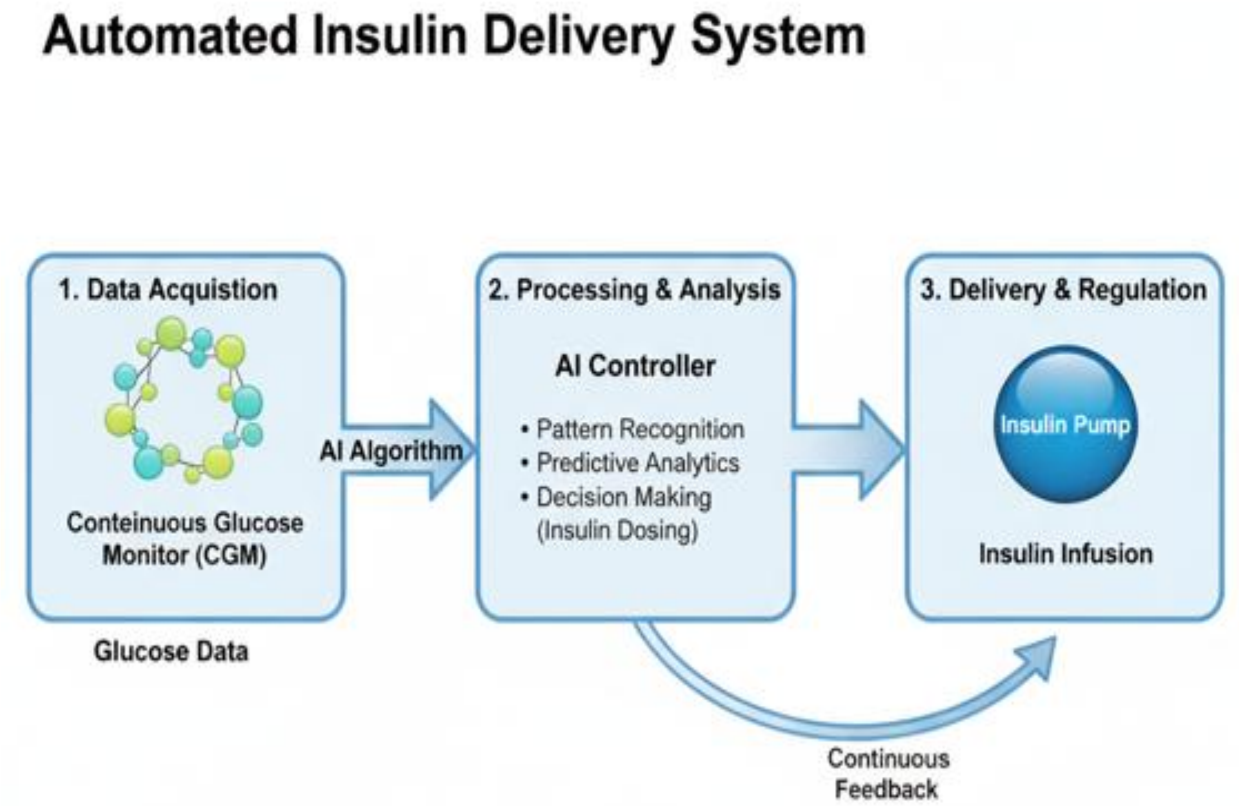

Figure 3: Automated insulin delivery system

Cardiac rehabilitation (CR): Cardiac rehabilitation (CR) is a thorough, evidence-driven program that combines exercise training, health education, promotion of physical activity, and counseling to effectively manage cardiovascular risk factors. In this context, wearable devices are essential as they monitor physiological functions such as heart rate (HR), movement, sleep, ECG analysis, and more, thereby providing valuable biometric data. Although there are challenges such as inconvenience and costs related to in-person sessions, wearable devices have the potential to improve accessibility and affordability, enabling reliable care from the comfort of patients' homes. The most frequently utilized wearable devices in CR include HR monitors, ECG monitors, accelerometers, pedometers, and health watches.

These devices assist in various facets of CR by offering real-time data that supports the remote monitoring and management of patient progress. Home-based cardiac rehabilitation (HBCR) is emerging as a viable alternative to center-based programs, bolstered by evidence indicating significant enhancements in cardiovascular health metrics when utilizing wearable ECG or HR monitoring devices. For example, a meta-analysis involving 15 randomized controlled trials (RCTs) with 1,314 participants underscored the considerable advantages of HBCR employing wearable technology. Notable improvements were recorded in left ventricular ejection fraction (MD = 2.12, 95% CI 1.21, 3.04), six-minute walk distance (MD = 40.00 meters, 95% CI 21.72, 58.29), and peak oxygen intake (MD = 2.24 ml/(min kg), 95% CI 1.38, 3.10) when compared to traditional center-based rehabilitation. Additionally, another study concentrating on patient post-ablation for atrial fibrillation (AF) revealed that tele-monitored CR was effective in enhancing cardiovascular fitness [16].

COPD: Ensure global health management is conducted equitably and sustainably. By examining the co-occurrence of keywords, this research uncovered that the primary focus of AI in managing chronic diseases revolves around various common chronic conditions, such as diabetes, hypertension, and chronic obstructive pulmonary disease (COPD) [17]. Chronic obstructive pulmonary disease (COPD) is a serious illness and ranks as the fourth leading cause of death globally [18]. Chronic obstructive pulmonary disease (COPD) is a prevalent and progressive respiratory disorder marked by persistent breathlessness, a gradual deterioration in lung function, and a diminished quality of life. In 2019, COPD was responsible for 3.23 million deaths globally, making it the third-leading cause of mortality. The worldwide estimated prevalence stands at 11.7%, with projections indicating an increase due to the aging global population and rising rates of both smoking and non-smoking exposures in low- and middle-income countries (LMICs). Relevant risk factors include cigarette smoke, occupational exposure to harmful particles, and both outdoor and indoor air pollution.

The natural progression of COPD is characterized by a gradual decline in lung function over time, accompanied by acute episodes of heightened symptoms and physiological changes known as exacerbations of COPD (ECOPDs). While ECOPDs are significant clinical events in acute settings, frequent and severe occurrences can result in irreversible airway damage and a decline in chronic lung function. The overall incidence of ECOPDs and hospitalizations due to COPD continues to rise, partly due to the increasing prevalence of COPD and the emergence of more severe disease forms associated with longer life expectancies. For instance, between 2010 and 2015, the hospitalization rate for ECOPDs rose from 83 to 86 per 100,000 individuals, and COPD remains a leading cause of hospitalization among all adult chronic diseases. The substantial impact of hospitalizations on the total cost of COPD, which amounts to an astonishing $50 billion in the United States alone, underscores the significant burden COPD places on healthcare systems [19].

Covid-19: The COVID-19 pandemic has underscored the capabilities of AI and IoT in managing crises.
These technologies have played a crucial role in tracking the virus's spread, overseeing infected individuals, and enhancing hospital resource allocation. AI systems have been employed to forecast infection patterns, simulate healthcare system capacity, and evaluate clinical data for quicker and more precise diagnostics. AI-powered image analysis tools were utilized to examine chest x-rays and CT scans for indications of COVID-19-related pneumonia, thereby shortening diagnosis times and improving patient outcomes.

At the same time, IoT-enabled wearable devices facilitated the remote monitoring of patients exhibiting mild COVID-19 symptoms, thereby decreasing the necessity for hospital visits and consequently reducing the risk of virus transmission. Patients' oxygen saturation, body temperature, and heart rate were continuously monitored, with healthcare providers being notified of any irregularities. Figure 4 illustrates the framework of IoT-enabled healthcare for monitoring COVID-19 patients [20].

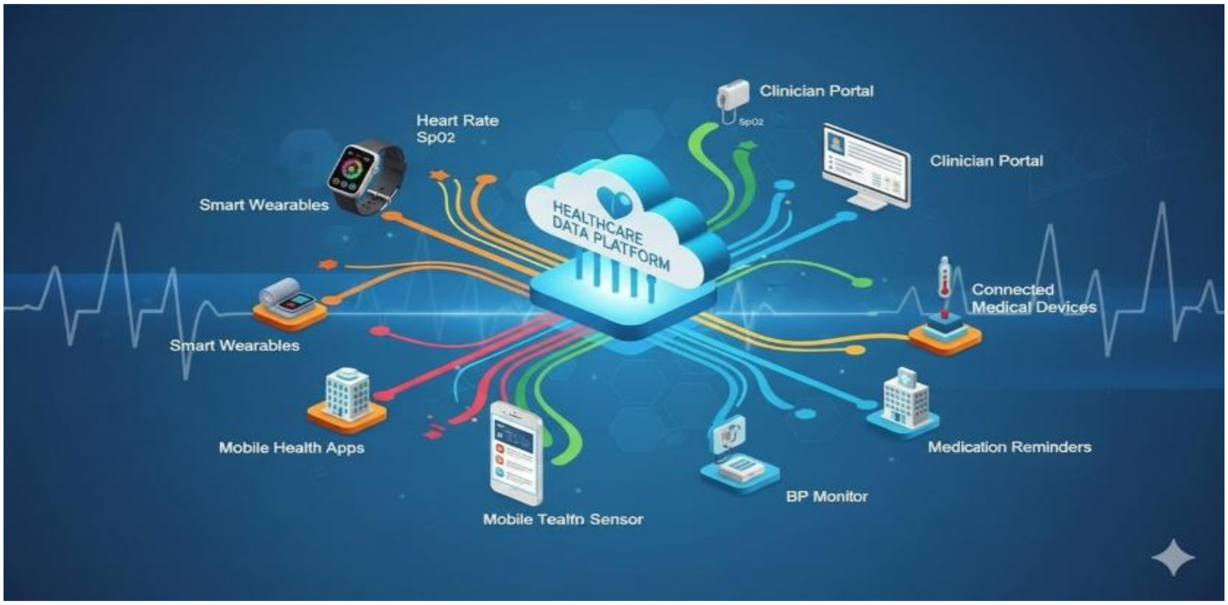

Figure 4: framework of IoT-enabled healthcare for monitoring COVID-19 patients

Hypertension: Hypertension, commonly referred to as high blood pressure, is a major risk factor for cardiovascular diseases. A direct correlation exists between blood pressure levels and the likelihood of developing cardiovascular conditions, including coronary artery disease and stroke (Lewington et al., 2002; Campbell et al., 2012) [21].

Diagnosis criteria: Two or more elevated readings recorded at two different appointments or locations [22]. Table 3 depicts stages of hypertension.

Table 3: Different stages of Hypertension

Blood Pressure Category	Systolic Pressure (top number)	Diastolic Pressure (bottom number)
Normal 🟢	Below 120 mmHg	AND Below 80 mmHg
---	---	---
Elevated ⚠️	Between 120 and 129 mmHg	AND Below 80 mmHg
---	---	---
Hypertension Stage 1 🟠	130 to 139 mmHg	OR 80 to 89 mmHg
---	---	---
Hypertension Stage 2 🔴	140 mmHg or greater	OR 90 mmHg or greater
---	---	---
Hypertensive Crisis 🚨	Above 180 mmHg	AND/OR Above 120 mmHg

Hypertension is a significant factor contributing to mortality and disability. Despite frequent interactions with healthcare providers, the majority of individuals with hypertension do not achieve controlled blood pressure (BP). Regular monitoring of BP at home may serve as a more reliable indicator of cardiovascular risk compared to sporadic measurements taken in a clinical setting, and it can help detect both masked hypertension and white coat hypertension. The evidence-based 2017 joint guidelines from the American College of Cardiology (ACC) and the American Heart Association (AHA) advocate for the use of out-of-office BP measurements to confirm diagnoses and adjust BP-lowering medications alongside other clinical interventions. Table4 shows various applications of AI in healthcare. Implementing home BP monitoring in conjunction with clinical team members who can enhance hypertension management has resulted in lower BP levels and improved control of hypertension [21].

Table 4: application of AI in healthcare.

Application	AI Component	IoT Device	Impact
Diabetes Management	Machine learning algorithms for glucose prediction	Continuous Glucose Monitors (CGMs)	Improved glycemic control via AI-driven insulin regulation.
Cardiovascular Monitoring	AI-based predictive analytics for detecting arrhythmias	Wearable ECG monitors	Early detection and intervention, reducing mortality risk.
Hypertension Management	AI algorithms for blood pressure prediction	Blood pressure cuffs linked with IoT	Automated detection of anomalies, enabling timely interventions.
Elderly Care	AI-powered fall detection and health tracking	IoT sensors in homes, wearable devices	Reduced emergency hospital visits, improved safety.

IV. DISCUSSION

The incorporation of Artificial Intelligence (AI) into remote patient monitoring (RPM) has transformed the management of chronic illnesses by facilitating continuous, data-informed, and individualized care.

Chronic ailments such as diabetes, hypertension, heart failure, and COPD necessitate ongoing monitoring and prompt interventions—requirements that conventional healthcare systems frequently struggle to fulfill.

AI-driven RPM systems address this shortcoming by evaluating real-time data from wearable sensors, mobile applications, and Internet of Medical Things (IoMT) devices, enabling early identification of clinical decline and more proactive treatment modifications.

Machine learning algorithms are capable of detecting subtle physiological variations—such as heart rate variability or glucose level changes—that may indicate potential complications, often prior to the onset of symptoms.

This predictive ability aids in decreasing hospital readmissions and emergency room visits while empowering patients to take an active role in managing their health.

Furthermore, AI improves personalization by amalgamating individual and population-level data to customize treatment suggestions.

Virtual assistants and chatbots also facilitate medication adherence and patient education, thereby enhancing long-term health outcomes.

Nonetheless, various obstacles hinder the broad implementation of these technologies. Data privacy and cybersecurity continue to be significant concerns, given the substantial amounts of patient information that are stored and transmitted electronically. Algorithmic bias stemming from limited or unrepresentative datasets can lead to disparities in care, while interoperability challenges between different monitoring systems and electronic health record (EHR) platforms impede seamless data integration. Furthermore, the clinical validation and acceptance of AI tools by professionals are still in development, necessitating additional research, transparency, and training for physicians.

Future developments should prioritize explainable AI (XAI) models that improve interpretability and foster trust, alongside the incorporation of multimodal data to provide more holistic health insights. Cooperation among healthcare professionals, data scientists, and policymakers will be crucial to guarantee the safe, ethical, and fair implementation of AI technologies in remote patient care.

V. CONCLUSION

AI-powered remote monitoring systems signify a significant transformation in the management of chronic illnesses, transitioning healthcare from a reactive approach to a proactive and predictive framework.

By utilizing continuous data streams, machine learning techniques, and advanced analytics, these systems facilitate the early identification of complications, tailored treatment plans, and enhanced patient involvement.

The advantages that arise from this include fewer hospital admissions, reduced healthcare expenses, and an improved quality of life for patients.

Nevertheless, to fully harness the capabilities of AI in remote monitoring, it is necessary to address key challenges concerning data privacy, transparency of algorithms, interoperability, and clinical validation.

A collaborative approach that merges technological advancements with ethical and regulatory considerations will be crucial in establishing trust and ensuring the safety of patients.

In summary, although AI-driven remote monitoring is still in its developmental stages, its incorporation into chronic disease management holds the promise of revolutionizing healthcare delivery on a global scale. As the technology evolves, its careful and fair implementation will be vital in fostering more efficient, patient-focused, and sustainable healthcare systems.

REFERENCE

[1] Walker Rachael C., Tong Allison, Howard Kirsten, Palmer Suetonia C., “Patient expectations and experiences of remote monitoring for chronic diseases: Systematic review and thematic synthesis of qualitative studies”, International Journal of Medical Informatics, ELSEVIER.

[2] Ellahham Samer, MD, “Artificial Intelligence: The Future for Diabetes Care”, THE AMERICAN JOURNAL OF MEDICINE.

[3] Bashi Nazli, RN, MAppSc; Karunanithi Mohanraj, PhD; Fatehi Farhad, MD, PhD; Ding Hang, PhD; Walters Darren, MD, PhD “Remote Monitoring of Patients With Heart Failure: An Overview of Systematic Reviews”, JOURNAL OF MEDICAL INTERNET RESEARCH.

[4] Kalusivalingam Kumar Aravind, Sharma Amit, Patel Neha, Singh Vikram “Enhancing Remote Patient Monitoring Systems with Deep Learning and Reinforcement Learning Algorithms”.

[5] XIE Yi, LU Lin, GAO Fei, HE Shuang-jiang, ZHAO Hui-juan, FANG Ying, YANG Jia-ming , AN Ying, YE Zhe-wei, DONG Zhe, “Integration of Artificial Intelligence, Blockchain, and Wearable Technology for Chronic Disease Management: A New Paradigm in Smart Healthcare”, Current Medical Science, DOI https://doi.org/10.1007/s11596-021-2485-0

[6] Patel Prachi M, Green Maja, Tram Jennifer, Wang Eugene, Murphy Melissa Zhu, Abd-Elsayed Alaa & Chakravarthy Krishnan. “Beyond the Pain Management Clinic: The Role of AI Integrated Remote Patient Monitoring in Chronic Disease Management – A Narrative Review”, Journal of Pain Research, to link to this article: https://doi.org/10.2147/JPR.S494238

[7] Alam Md Ashraful, Sohel Amir, Uddin Mohammed Majbah, Sidiki Amir, “BIG DATA AND CHRONIC DISEASE MANAGEMENT THROUGH PATIENT MONITORING AND TREATMENT WITH DATA ANALYTICS”, Academic Journal on Artificial Intelligence,

Machine Learning, Data Science and Management Information Systems Vol 01 | Issue 01 | October 2024 Doi: 10.69593/ajaimldsmis. v1i01.133 Page:77-94.

[8] Bacha Ahmad, Zainab Hira, “AI for Remote Patient Monitoring: Enabling Continuous Healthcare outside the Hospital”, Global Journal of Computer Sciences and Artificial Intelligence, Volume 1, Number 1, January, 2025.

[9] Boppana Venkat Raviteja, “Role of IoT in Remote Patient Monitoring Systems, Advances in Computer Sciences”, Vol. 2 (2019) https://academicpinnacle.com/index.php/acs.

[10] Yousaf Muhammad, “The Future of Healthcare: AI and IoT in Managing Chronic Diseases and Enhancing Patient Care”, Research, November 2022, DOI: 10.13140/RG.2.2.14763.86560

[11] Luz A., & Gimah M. “AI-Driven Early Detection Systems for Chronic Diseases”. Preprints.org. https://doi.org/10.20944/preprints202501.2144.v1

[12] Shaik Thanveer, Tao Xiaohui, Higgins Niall, Li Lin, Gururajan Raj, Zhou Xujuan, Acharya Rajendra U, “Remote patient monitoring using artificial intelligence: Current state, applications, and challenges”, DOI:10.1002/widm.1485, WILEY.

[13] El-Rashidy N., El-Sappagh S., Islam S. M. R., El-Bakry H. M., & Abdelrazek S. “Mobile Health in Remote Patient Monitoring for Chronic Diseases: Principles, Trends, and Challenges”. Diagnostics, 11(4), 607. https://doi.org/10.3390/diagnostics11040607

[14] Luz Ayuns, Gimah Mathew “AI-Driven Early Detection Systems for Chronic Diseases” ,29 January 2025, doi: 10.20944/preprints202501. 2144.v1

[15] Ramesh J., Aburukba R., & Sagahyroon A. “A remote healthcare monitoring framework for diabetes prediction using machine learning”. Healthcare Technology Letters, 8(3), 45–57. https://doi.org/10.1049/htl2.12010

[16] Jafleh E, A Alnaqb , F. A Almaeeni, H. A, Faqeeh S, Alzaabi M. A, & Al Zaman, K. “The role of wearable devices in chronic disease monitoring and patient care: A comprehensive review”. Cureus, 16(9), e68921. https://doi.org/10.7759/cureus.68921.

[17] Pan, M., Li, R., Wei, J., Peng, H., Hu, Z., Xiong, Y., Li, N., Guo, Y., Gu, W., & Liu, H. (2025). “Application of artificial intelligence in the health management of chronic disease bibliometric analysis”. Frontiers in Medicine, 11, Article 1506641. https://doi.org/10.3389/fmed.2024.1506641.

[18] Cooper C. B., Sirichana W., Arnold M. T., Neufeld E. V., Taylor M., Wang X., & Dolezal B. A. “Remote patient monitoring for the detection of COPD exacerbations. International Journal of Chronic Obstructive Pulmonary Disease”, 15, 2005–2013. https://doi.org/10.2147/COPD.S256907.

[19] Coutu F.-A., Iorio O. C., & Ross B. A. “Remote patient monitoring strategies and wearable technology in chronic obstructive pulmonary disease”. Frontiers in Medicine, 10, 1236598. doi:10.3389/fmed.2023.1236598

[20] Dang A. T., & Dang T. T. “Harnessing AI and IoT for the future of healthcare: A comprehensive review on chronic disease management and pandemic response [Preprint]”. Preprints.org. https://doi.org/10.20944/preprints202409.2451.v1

[21] Petito L. C., Anthony L., Peprah Y. A., Lee J. Y., Li J., Sato H., & Persell S. D. (2023). “Remote physiologic monitoring for hypertension in primary care: A prospective pragmatic pilot study in electronic health records using propensity score matching.” JAMIA Open, 6(1), ooac111. https://doi.org/10.1093/jamiaopen/ooac111

[22] Knauf T., Rue J., & Lundeen H. (2021), “Management of hypertension RPM and SMBP: Self-measure BP pilot at Trinity Health.” [Unpublished presentation slides].