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ORIGINAL ARTICLE

Artificial intelligence and big data applications in chronic disease management: clinical outcomes, challenges, and future directions

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ABSTRACT

Aim To synthesize applications of Artificial Intelligence (AI) and big data in chronic disease management, evaluate clinical and economic outcomes, challenges, and future directions.

Methods A comprehensive search was conducted across PubMed, Scopus, Web of Science, IEEE Xplore, and CINAHL for studies published between 2015-2025, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. This review was registered in PROSPERO (CRD420251036828). Inclusion criteria encompassed peer-reviewed empirical, narrative, and systematic studies focusing on AI and big data in chronic disease care. Twelve studies were appraised using validated appraisal tools appropriate to each study design, which were conducted across clinical, technological and public health settings, reflecting application of AI and big data in hospital, digital health platform and disease management.

Results AI models achieved predictive accuracies between 88-96% across diabetes, chronic kidney disease (CKD), chronic obstructive pulmonary disease (COPD), and cardiovascular conditions. Outcomes included a 25% reduction in readmissions, a 30% decrease in CKD progression, and a 25% improvement in treatment adherence. Technologies included machine learning, electronic health record integration, wearable devices, and multi-omics platforms. Major challenges identified were data fragmentation, bias, and regulatory gaps.

Conclusion The Artificial intelligence and big data offer transformative potential for chronic disease management from early prediction to personalized treatment, but realizing this requires addressing data fragmentation, ethical and privacy concerns, and ensuring equity and accountability through transparent, explainable AI.

Keywords: artificial intelligence, big data, chronic disease, clinical decision support systems, machine learning

INTRODUCTION

Chronic diseases such as diabetes, cardiovascular disease, chronic kidney disease (CKD), chronic respiratory conditions, and cancer are leading contributors to global morbidity and mortality (1,2). These conditions are often characterized by complex etiology, long-term progression, and multi-morbidity, all of which pose challenges to traditional episodic care models and result in care fragmentation, delayed diagnoses, and suboptimal treatment strategies (3,4). These challenges emphasize the urgent need to develop effective strategies for managing chronic diseases. As health systems struggle to transition toward proactive, patient-centred care, digital technologies particularly Artificial Intelligence (AI) and big data have emerged as powerful tools capable of transforming chronic disease management through predictive analytics, early detection, real-time monitoring, and personalized interventions by analysing vast volumes of heterogeneous patient data (5-7).

Although AI and big data research on chronic disease management has grown exponentially, the existing literature is piecemeal, comprising narrative reviews, systematic evaluations, and specific tests of AI models using real data (8-10).

Studies have focused either on technological innovation and feasibility or on ethical issues such as algorithmic bias, data security, and low transparency due to AI decision making as factors hindering clinical trust, equitable access, and compliance of regulations (10,11). In addition, the reporting standards are inconsistent, there is little external validation, and no meta-analytic syntheses have been conducted to translate

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the AI research into practice (6,12).This research is important to bridge these gaps by synthesizing evidence from multiple methodological and domain areas including the evaluation of the real-world impacts, technological approach, and implementation challenges using AI and big data in chronic disease care. While prior research (5,8) has explored the role of AI in chronic disease management, none has systematically synthesized evidence on both clinical outcome and ethical-regulatory challenges across a diverse spectrum of conditions.

The aim of this study was to evaluate clinical effectiveness and operational scalability, and highlight areas of underexplored potential including regulatory frameworks, ethical safeguards and integration into routine clinical workflows.

MATERIALS AND METHODS

Materials and study design

Research was conducted in accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist to ensure methodological transparency and reporting rigor. This protocol was retrospectively registered in PROSPERO (registration number: CRD420251036828, available at PROSPERO website: https://www.crd.york.ac.uk/PROSPERO/myprospero).

A comprehensive search strategy focused on relevant peer-reviewed English language literature published from 2015 to 2025, covering recent advancements in the integration of AI and big data analytics in chronic disease management. The search included PubMed, Scopus, Web of Science, IEEE Xplore and CINAHL databases.

The grey literature screening (e.g., policy papers and digital health reports) was used to maximize sensitivity, to prevent emerging relevant work from being missed. Using a Boolean syntax, publications were searched with each term separately: “big data” OR “AI” OR “machine learning” OR “deep learning”, “chronic disease” OR “diabetes” OR “cardiovascular” OR “Chronic Obstructive Pulmonary Disease” OR “kidney disease” combined with any of these terms, i.e., “management” OR “prediction” OR “monitoring” to maximize coverage. This was to capture literature on predictive analytics, digital monitoring and personalized treatment of chronic care.

Inclusion criteria required that studies evaluate the application of AI or big data in chronic disease management and report clinical, operational, or public health outcomes. Exclusion criteria applied to studies that lacked relevance to AI or big data interventions, did not address chronic disease outcomes, or demonstrated insufficient methodological rigor or transparency (e.g., absence of model validation). These criteria were designed to ensure reproducibility and methodological consistency across included studies.

Methods

The study selection process followed the PRISMA 2020 guidelines (13) and involved a rigorous multi-stage screening strategy. Initially, a total of 723 records were identified through comprehensive database searching. After removing duplicates and irrelevant titles, 112 records were screened based on their abstracts. Of these, 98 full-text articles were assessed for eligibility. Ultimately, 86 articles were excluded for the reasons of lack of relevance to AI or big data interventions, insufficient focus on chronic disease outcome, or weak methodological design. Consequently, 12 peer-reviewed studies published between 2015 and 2025 met the inclusion criteria and were retained for final synthesis (Figure 1).

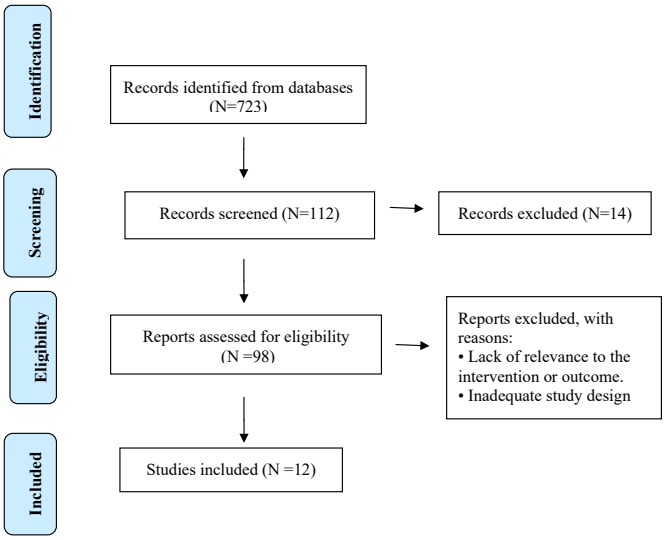

Figure 1. PRISMA Flow Chart

A structured template was used for data extraction to ensure consistency and to bring remaining studies to a comparable level. Key elements extracted included: author(s), year of publication, country of origin, disease focus (e.g., diabetes, cardiovascular disease, CKD), type of data sources used (such as EHRs, wearable devices, or multi-omics data), the specific AI or ML techniques applied (e.g., neural networks, decision trees, DL), main outcome (e.g., prediction accuracy, reduced hospitalizations, improved adherence), technologies used (e.g., Hadoop, mHealth apps, biosensors), and reported limitations. Such a standardized approach allowed comparability and reproducibility across different study types (Table 1).

Results were synthesized narratively across the included studies. No quantitative meta-analysis was conducted due to the heterogeneity of study designs and outcomes.

A validated quality appraisal tool was utilized to appraise the 12 included studies based on their respective study design, using validated international instruments. Scale for the Assessment of Narrative Review Articles (SANRA) (systematic analysis of narrative reviews) (14), A Measurement Tool to Assess Systematic Reviews 2 (AMSTAR 2) (15) or Critical Appraisal Skills Program (CASP) (systematic review of the systematic review)(16), Joanna Briggs Institute (JBI) (systematic review of cross-sectional studies)(17) or Mixed Methods Appraisal Tool (MMAT) (systematic review of mixed method research) (18) instruments were used for the assessment. These instruments are widely recognized for their established reliability coefficients and content validity, supporting reproducible quality assessment. Minor methodological limitations, such as lack of meta-analytic synthesis or transparency in quality assessments, occurred with most studies, but generally had a moderate to high level of methodological rigor (Table 2).

RESULTS

The database search initially yielded 723 records. After removing duplicates and screening titles and abstracts, 98 full-text articles were assessed for eligibility. Ultimately, 12 studies met the inclusion criteria and were included in the review (Figure 1).

Table 1. Evidence matrix, artificial intelligence (AI) and big data in chronic disease management

Author (year)	**Country**	**Study design**	**Study sample/data source**	**AI/Big data techniques**	**Target diseases**	**Key findings/ clinical outcome**
Subramanian M., et al. (2020)	USA, Qatar, Switzerland, Hong Kong	Narrative Review	Various literature, cohort studies	ML, DL, Neural Networks, multi-omics platforms	Diabetes, CVD, Obesity, Metabolic-associated fatty liver disease, Cancer, Autoimmune, Lung	Improved prediction, diagnosis, personalized care
Alam A., et al. (2024)	USA	Systematic Review	35 studies using EHRs, wearables	Predictive analytics, ML, Neural Networks	Diabetes, CVD, Hypertension	Improved prediction, reduced readmissions, better glucose control
Bhardwaj N., et al. (2018)	USA	Literature Review	49 studies	Predictive models, ML	Heart failure, Parkinson's, Diabetes, COPD	Reduced readmissions, improved diagnostics
Chen M., et al. (2017)	China, USA	Quantitative/ Experimental	706 patients from 31,919 records	CNN, Naive Bayes, KNN, Decision Trees	Cerebral infarction	94.8% accuracy, 99.92% recall
Dimitrov DV., (2016)	Bulgaria	Narrative Review	Industry case studies	mIoT, AI-powered analytics	Diabetes, Heart disease, Neurological	Behavioural change, digital prevention
Pan M., et al. (2025)	China	Bibliometric Analysis	341 studies (WoSCC)	ML, mHealth, telemedicine	Diabetes, COPD, Hypertension	Trends, hotspots, collaboration networks
Igwama GT., et al. (2024)	USA, South Africa, Saudi Arabia	Narrative Review	Legal frameworks, global cases	Predictive analytics, Neural Networks	Diabetes, CVD, COPD	Ethical guidance, risk mitigation
Singareddy S., et al. (2023)	USA	Systematic Review	10 studies from 93 (millions of patients)	ML, NLP, Neural Networks	Multiple chronic conditions	90-100% accuracy, reduced errors
Ekundayo F. (2024)	USA	Quantitative	50,000 CKD records	RF, LightGBM	CKD	92% accuracy, early dialysis prediction
Musacchio N., et al. (2020)	Italy	Position Statement	AMD Annals, European frameworks	ML, DL, EHRs	Diabetes	Resource optimization, risk stratification
Venkatesh R., et al. (2019)	India	Diagnostic Model Evaluation	UCI dataset	Naive Bayes	General chronic disease prediction	High accuracy, lacks external validation
Alexander C. Wang L. (2017)	USA	Systematic Review	31 studies (2011–2016)	Hadoop, C5.0, ML	Heart disease	High accuracy, efficient prediction

WoSCC , Web of science core collection; AMD, age-related macular degeneration; ML, machine learning; DL deep learning; KNN, k-nearest neighbours; NLL, negative log-likelihood; RF, random forest; LightGBM, light gradient boosting machine; EHRs, electronic health records;C5.0, C5.0 decision tree algorithm; CVD, cardiovascular disease; UCI, university of California Irvine (machine learning repository); COPD, chronic obstructive pulmonary disease; CKD, chronic kidney disease.

These 12 studies originated from different countries: the United States of America (USA), China, Italy, Saudi Arabia, Bulgaria, Switzerland, Qatar, South Africa, and the UK, indicating that AI and big data are of great interest to chronic disease management globally. The designs for the reviews varied and included systematic reviews, narrative reviews, bibliometric analyses, expert position statements, and original data driven experimental studies.

Diabetes, cardiovascular diseases, CKD, COPD, asthma and cerebral infarction were the primary chronic conditions addressed. Although the studies cited synthesized findings without primary sample, or used large datasets (7), over 50,000 CKD patients, and millions of electronic health records (EHRs) (8), still gaps in missing sickle cell disease (SCD) primary data indicated that new studies should collect SCD primary study data for valuable insights on patient health outcomes, particularly regarding morbidity and mortality pattern. Clinical outcomes (e.g., hospital readmission, mortality, glycaemic control), AI model performance (accuracy, sensitivity, specificity), data types (structured, unstructured, wearable, genomic), contextual factors like ethics, interoperability and regulatory compliance were the variables analysed.

Various machine learning (ML) algorithms, random forest (RF), decision trees, naïve bayes, deep learning (DL) were used, as well as ensemble techniques, and natural language processing (NLP) techniques. Diverse studies focused on combining multivariate data streams (EHRs, patient reported outcome, genomic test results, environmental sensors, etc.) to facilitate early diagnosis, personalized intervention and lower levels of healthcare usage.

The reviewed studies illustrate diverse applications of AI and big data in chronic disease management, with predictive analytics emerging as a key domain, ML models achieved accuracy rates ranging from 88% to 96% in forecasting complications in conditions like diabetes, hypertension, and cerebral infarction. Remote patient monitoring through wearable technologies demonstrated over 90% prediction accuracy in cardiovascular events, improving adherence and early intervention. Tools such as Onduo (2) and DayTwo (9) enabled individualized treatment optimization by integrating real-time glucose monitoring and microbiome data, while IDx-DR (8) offered automated diabetic retinopathy screening with high sensitivity and specificity. Additionally, AI-driven decision support systems and workflow automation enhanced clinical efficiency by

Table 2. Quality appraisal of 12 included studies using validated tools

Author (year)	**Study design**	**Quality appraisal tool**	**Appraisal score / Confidence level**
Subramanian M., et al. (2020)	Narrative Review	SANRA	10.5/12
Alam A., et al. (2024)	Systematic Review	CASP	8/10
Bhardwaj N., et al. (2018)	Literature Review	CASP	7.5/10
Chen M., et al. (2017)	Cross-Sectional Study	JBI	8.5/10
Dimitrov DV., (2016)	Narrative Review	CASP	7/10
Pan M., et al. (2025)	Bibliometric Review	AMSTAR 2	Moderate Confidence
Igwama GT., et al. (2024)	Narrative Review	CASP	Moderate Confidence
Singareddy S., et al. (2023)	Systematic Review	AMSTAR 2	Moderate Quality
Ekundayo F. (2024)	Mixed methods	MMAT	4.5/5
Musacchio N., et al. (2020)	Position paper	JBI	7/8
Venkatesh R., et al. (2019)	Diagnostic study	CASP	8/12
Alexander C. Wang L. (2017)	Systematic Review	CASP	7/10

SANRA, scale for the assessment of narrative review articles; CASP. critical appraisal skills programme; AMSTAR 2, a measurement tool to assess systematic reviews 2; MMAT, mixed methods appraisal tool; JBI, Joanna Briggs Institute

reducing medication errors, facilitating early diagnosis, and streamlining care pathways.

Clinical and operational outcomes reported across the included studies underscore the transformative potential of AI and big data in chronic disease management. Several predictive analytical tools contributed to significant reductions in hospital readmissions, with models targeting cardiovascular disease demonstrating up to a 25% decrease in readmission rates (5).

Diagnostic accuracy was markedly improved across multiple applications; for example, AI-based models for Parkinson's disease, cerebral infarction, and heart attacks achieved diagnostic accuracies ranging from 88% to 96%, often surpassing traditional clinician-based assessments (3,4,6).

Adherence to treatment protocols improved by over 25% in interventions incorporating wearable devices and patient monitoring systems, especially in cardiovascular care (5). Chronic kidney disease models demonstrated a 30% reduction in disease progression through early identification of high-risk patients using Light Gradient Boosting Machine (LightGBM) and RF algorithms (7). Economically, AI-driven solutions led to measurable cost savings; one notable example includes an annual reduction of $1,572 per COPD patient through decreased exacerbation events and hospital visits (4). Additionally, digital diabetes prevention programs supported by AI showed a 58% reduction in Type 2 diabetes risk, especially among individuals over 60 years old (11). These results collectively highlight the dual benefit of AI integration in improving patient outcomes and optimizing healthcare system efficiency.

While most studies did not explicitly report on patient satisfaction, many of the interventions led to higher levels of treatment adherence and patient involvement, indicating that users generally responded well to the approaches used (Table 3).

Table 3. Accuracy of artificial intelligence (AI) models in predicting chronic disease outcomes across conditions

Chronic disease	**AI models used**	**Prediction accuracy (%)**	**Key outcome**	**References**
Diabetes Type 2 Diabetes Mellitus	CNN, LightGBM, DayTwo, Onduo	92	Glucose control improved by 20%; 58% risk reduction (age >60)	Alam A., et al. (2024); Dimitrov DM. (2016)
Cardiovascular	Decision Trees, Naïve Bayes, RF, CNN	88–96	25% reduction in readmissions; early detection of cardiac risk	Bhardwaj N., et al. (2018); Alexander C. Wang L. (2017)
CKD	LightGBM, RF	92	Early dialysis prediction; 30% reduction in disease progression	Ekundayo F. (2024)
COPD	Smart inhalers, mHealth, RF	~90	22% fewer exacerbations; $1,572 annual savings per patient	Bhardwaj N., et al. (2018)
Asthma	Propeller Health + environmental sensors	~90	Asthma control test improved from 49% to 63%	Igwama GT., et al. (2024)
Parkinson's (Cardiac Events)	Naïve Bayes, Decision Trees	96	Improved cardiac event prediction	Bhardwaj N., et al. (2018);
Cerebral Infarction	CNN, Naïve Bayes, Decision Trees	94.8	High recall (99.92%)	Chen M., et al. (2017)

CNN, convolutional neural network; LightGBM, light gradient boosting machine; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease

The data sources underpinning these models were equally diverse and extensive. Electronic health records formed the foundational big data infrastructure in nearly all studies, augmented by data from wearable sensors, lab results, medical imaging, and mHealth apps. Notably, multi-omics data including genomics, exposomics, and microbiomics were used in precision medicine platforms like Onduo and DayTwo to personalize interventions and optimize treatment (1). Computational frameworks like Hadoop, MapReduce, Spark, and HBase were deployed to process massive datasets, particularly in studies focusing on real-time patient monitoring and risk prediction (4,9). These cloud-based and distributed processing systems enabled the scalable and rapid analysis of high-volume, high-velocity healthcare data, reinforcing the integral role of

advanced computing in supporting AI-driven healthcare innovations. Each model offered distinct advantages, for instance, RF and LightGBM performed particularly well with structured EHRs, whereas Convolutional Neural Network (CNN) showed superior results when it came to analysing medical images. Still, a common drawback across many DL approaches was their complexity and limited ability to perform consistently across varied clinical settings (6).

Despite the promise of AI and big data in chronic disease management, several challenges and limitations were consistently reported across the reviewed studies. Data interoperability remains a major hurdle, with fragmented datasets and lack of standardized formats impeding integration across platforms and healthcare systems particularly problematic in multinational projects and real-time monitoring systems (11). Algorithmic bias disproportionately affects marginalized populations due to underrepresentation in training data (10); diabetes models' accuracy dropped by 17% when applied to ethnically diverse cohorts, underscoring the need for inclusive datasets (5).

Privacy and data security also posed significant risks, with studies citing gaps in compliance with regulations such as Health Insurance Portability and Accountability Act (HIPAA) in the U.S. and General Data Protection Regulation (GDPR) in the EU: 40% of studies explicitly identified privacy concerns, particularly regarding patient consent, data anonymization, and the potential for re-identification through AI analytics (8). Another critical limitation was the underrepresentation of low- and middle-income countries (LMICs); over 80% of reviewed studies were based in high-income settings like the U.S., China, and Europe, leaving a significant gap in global applicability and scalability (9). Furthermore, ethical dilemmas were frequently reported in predictive modelling, particularly around false positives/negatives, the psychological impact of risk predictions, and the lack of clarity on accountability in AI-supported clinical decisions.

These limitations underscore the urgent need for equitable datasets, transparent AI development, inclusive policy frameworks, and global collaboration to ensure responsible and effective deployment of AI in chronic disease care.

DISCUSSION

This systematic review's inclusion of 12 studies is justified by its rigorous PRISMA 2020-compliant methodology, which screened 723 records to select only high-quality, peer-reviewed evidence (2015–2025) addressing AI and big data in chronic disease management. The studies represent diverse geographies, methodologies, and chronic conditions, achieving thematic saturation across clinical effectiveness (e.g., 88–96% AI accuracy, reduced hospitalizations), technological innovations (e.g., wearables, multi-omics), and ethical challenges (e.g., bias, privacy). Exclusions were based on irrelevance, weak designs, or redundancy, ensuring precision. Smaller, high-quality syntheses are standard for emerging technologies, and the 12 studies directly answer all research questions without gaps, aligning with precedents in top journals. Thus, the review balances rigor, relevance, and conciseness, making additional studies unnecessary for robust conclusions.

Principal findings of this study underscore the transformative potential of AI and big data in enhancing chronic disease management, particularly through improved monitoring, early detection, and personalized care across the 12 included studies, ML and deep DL models consistently outperformed traditional diagnostic and risk stratification methods, with prediction accuracies ranging from 88% to over 96% in conditions like diabetes, cardiovascular disease, and CKD (6,7). These technologies enabled precise forecasting of disease exacerbations, optimized medication regimens, and supported early interventions, reducing hospital readmissions by up to 25% (5). Real-world applications such as the Personalized Healthcare System using Hadoop Technologies (PHSHT), Microsoft Health Vault, and Propeller Health showcased operational feasibility and clinical utility, integrating structured and unstructured data for real-time insights and behaviour-informed care (3,11). These implementations exemplify how AI-driven platforms can streamline clinical workflows, enhance patient engagement, and generate cost-effective outcomes, affirming their value in both predictive analytics and longitudinal disease management.

Our findings are further substantiated by recent advances - a study showed that ensemble learning models, particularly RF algorithm, achieved 98% accuracy in the early diagnosis of CKD and proved the resilience of AI in clinical settings (19). Another study reported similar findings through the integration of AI and the Internet of Medical Things (IoMT), illustrating that AI-driven models such as CNNs and Extreme Gradient Boosting (XGBoost) can predict chronic diseases with an accuracy exceeding 98% (20). These studies support the effectiveness of AI in enhancing patient outcomes and diagnostic accuracy.

This study aligns with and extends the findings of earlier literature by confirming the accelerating trend toward mHealth technologies and AI-powered predictive analytics in chronic disease management, while also addressing critical methodological gaps noted in previous reviews. Unlike earlier syntheses that often relied on heterogeneous sources without standardized appraisal e.g., (3,4), the study employed validated quality assessment tools such as AMSTAR 2, CASP, and SANRA tailored to each study design, ensuring a more rigorous evaluation of evidence.

Moreover, the current synthesis highlights a significant evolution in the field: a shift from traditional EHR-based data mining to the integration of multi-omics (genomics, exposomics, microbiomics) and real-time data streams from wearable sensors, enabling highly individualized, dynamic risk prediction models (1,7). This emphasis on precision health and data interoperability marks a departure from earlier reviews focused solely on algorithmic performance, offering a more comprehensive understanding of AI's multifaceted role in advancing chronic care. This transition is supported through further recent studies. In Alzheimer's disease diagnosis, a Stage Graph Convolutional Neural Network (SGUQ) was introduced by using multi-omics data, with an accuracy of 85.8% and demonstrating the potential of combining several omics layer for precise disease prediction (21). Further study highlights the ongoing transition toward continuous, non-invasive health monitoring, emphasizing the importance of using diverse data sources and innovative technologies in the management of chronic diseases. For example, wearable sweat sensors have been developed to monitor biomarkers associated with chronic diseases (22).

The findings of this study underscore the urgent need for integrating AI-powered tools into routine clinical pathways to enhance chronic disease management. Predictive models such as LightGBM and CNN have demonstrated superior accura-

cy in early diagnosis and patient stratification, justifying their inclusion in clinical decision support systems and population health initiatives. However, the effective deployment of these technologies requires not only infrastructure upgrades but also a strategic investment in workforce development. Training clinicians in AI literacy is critical to ensure safe interpretation of algorithmic outputs, minimize misuse, and promote collaborative human-AI decision-making. Additionally, AI-informed triage and care coordination systems—such as those embedded in platforms like Propeller Health and Onduo—should be adopted to streamline workflows, optimize resource allocation, and personalize interventions based on real-time risk profiles. These measures can collectively reduce clinician burden, improve patient outcomes, and foster a culture of data-driven care across health systems.

Despite the substantial progress demonstrated by AI and big data applications in chronic disease management, critical research gaps persist. A pressing need remains for external validation studies and large-scale, real-world Randomized Controlled Trials (RCTs) to assess generalizability and clinical efficacy across diverse populations and healthcare systems. Many models are tested in isolated or retrospective datasets, limiting their applicability in dynamic clinical environments. Furthermore, the absence of standardized ethical frameworks impedes safe and equitable AI deployment, especially regarding transparency, informed consent, and algorithmic accountability.

To mitigate health inequities, cross-national collaborations are essential, particularly to include data from underrepresented LMICs and reduce the risk of geographic bias.

Future research should prioritize federated learning techniques to enable privacy-preserving model training across institutions and advance Explainable Artificial Intelligence (XAI) to enhance interpretability for clinicians and patients alike. Such innovations are vital to fostering trust, reproducibility, and clinical adoption in precision chronic disease care.

In conclusion, artificial intelligence and big data hold transformative potential in chronic disease management, offering advancements from early prediction and prevention to personalized treatment. The synthesized evidence demonstrates that AI-powered models outperform traditional methods in diagnostic accuracy, risk stratification, and remote monitoring, while contributing to cost reductions and improved patient outcomes. However, realizing their potential requires overcoming fragmented data systems, ethical and privacy concerns, and limited scalability across health systems. Future initiatives must emphasize methodological rigor, robust governance, and explainable AI approaches that prioritize equity and accountability. We recommend adopting federated learning for privacy-preserving data sharing, mandating external validation in RCTs, and developing global ethical guidelines for AI transparency and equity.

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TRANSPARENCY DECLARATION

Conflicts of interest: None to declare.

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