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ARTIFICIAL INTELLIGENCE-BASED SMART HEALTHCARE SYSTEMS FOR EARLY DISEASE PREDICTION

Tayyaba Fatima
BS, Department Islamic Studies, The Cosmic Degree College (For Women) ,University of Okara

ABSTRACT

Artificial Intelligence (AI)-based smart healthcare systems are transforming modern healthcare by enabling the early prediction of diseases, improving diagnostic accuracy, and supporting timely clinical decision-making. Traditional healthcare systems often depend on symptom-based diagnosis, periodic medical examinations, and manual interpretation of clinical information, which may delay the identification of diseases and reduce opportunities for preventive intervention. The integration of machine learning, deep learning, electronic health records, wearable devices, medical imaging, and Internet of Things (IoT) technologies provides new opportunities to identify disease-related patterns before severe symptoms develop. This research examines the role of AI-based smart healthcare systems in early disease prediction, with particular emphasis on cardiovascular diseases, diabetes, cancer, neurological disorders, and infectious diseases. It explores the technological foundations of intelligent healthcare, the applications of predictive analytics, the benefits of personalized monitoring, and the challenges associated with data quality, privacy, algorithmic bias, interpretability, and clinical integration. A structured literature-based research approach is proposed to synthesize relevant studies published between 2023 and 2025. The paper also considers the importance of clinical validation, responsible data governance, and collaboration between healthcare professionals and AI developers. The study aims to establish how intelligent healthcare systems can support proactive, patient-centered, and evidence-based medical services. It argues that AI can contribute substantially to early disease prediction when predictive models are developed using representative data, evaluated rigorously, and integrated into clinical workflows under appropriate professional supervision. The findings discussed in this paper are based on a conceptual synthesis of existing research rather than newly collected patient data or an independently conducted clinical experiment.

KEYWORDS: *Artificial Intelligence, Smart Healthcare Systems, Early Disease Prediction, Machine Learning, Deep Learning, Predictive Analytics, Electronic Health Records, Internet of Things, Wearable Health Devices, Precision Medicine, Clinical Decision Support Systems, Healthcare Data Analytics, Explainable AI, Data Privacy, Preventive Healthcare.*

INTRODUCTION

Healthcare systems worldwide are increasingly adopting digital technologies to improve the prevention, diagnosis, treatment, and monitoring of diseases. Conventional healthcare approaches frequently rely on patients reporting symptoms, attending medical consultations, and undergoing diagnostic examinations after a health problem has become noticeable. Although these approaches remain essential, they may not always identify diseases during their earliest stages. Albahri, A. S., Duhaim, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L., ... & Deveci, M. (2023). found that Many chronic conditions, including diabetes, cardiovascular disease, and certain cancers, can develop gradually and remain undetected for extended periods. Artificial Intelligence (AI) offers a promising approach to this problem by analyzing large volumes of medical information and identifying patterns that may indicate an increased probability of future disease. Smart healthcare systems combine AI with connected medical devices, digital health records, remote monitoring technologies, and clinical decision-support tools to create a more proactive healthcare environment. Rather than focusing exclusively on treating existing illness, these systems seek to support prevention and early intervention.Artificial intelligence refers to computational techniques that enable computer systems to perform tasks involving pattern recognition, prediction, classification,

International Journal Of
Artificial Intelligence And
Engineering Innovation
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and decision support. Within healthcare, machine learning algorithms can learn relationships between patient characteristics, laboratory measurements, medical histories, lifestyle factors, and disease outcomes. Deep learning models can also process complex information such as radiological images, electrocardiograms, pathology slides, and longitudinal physiological measurements. For example, predictive models may estimate an individual's risk of developing diabetes by examining glucose levels, body mass index, family history, and other relevant variables. Similarly, AI systems may identify suspicious features in medical images or detect abnormal changes in heart rhythm. These applications demonstrate the potential of AI to identify clinically relevant signals that may be difficult to recognize consistently through manual assessment alone. Nevertheless, a prediction indicates a probability or risk rather than a definitive diagnosis, and its clinical significance must be established through appropriate validation.

The effectiveness of AI-based disease prediction depends on the integration of multiple technological components. Electronic health records provide information about patient histories, previous diagnoses, prescriptions, laboratory tests, and clinical observations. Wearable devices and connected sensors can continuously or periodically measure indicators such as heart rate, physical activity, sleep patterns, oxygen saturation, and blood pressure, depending on the device. Medical imaging systems contribute additional information for identifying abnormalities, while cloud computing and secure data platforms can support the storage and processing of large datasets. IoT technologies facilitate communication between connected devices, enabling health information to be collected outside traditional hospital environments. When these data sources are combined appropriately, AI models can support longitudinal monitoring and identify changes that warrant further clinical assessment. However, integrating different sources also introduces technical difficulties, including inconsistent data formats, missing measurements, device inaccuracies, and differences in the quality of information collected across healthcare institutions.Early disease prediction is important because the timing of identification can influence treatment options, healthcare expenditure, disease progression, and patient quality of life. Detecting elevated cardiovascular risk before a major cardiac event, identifying diabetes before serious complications emerge, or recognizing suspicious cancer-related findings at an earlier stage may create opportunities for more timely intervention. AI-based prediction systems can help clinicians prioritize patients who may require additional screening, laboratory testing, or specialist consultation. They may also support personalized prevention strategies by considering combinations of risk factors rather than relying exclusively on generalized population-level recommendations. In remote and resource-constrained settings, properly designed digital tools may help healthcare professionals monitor patients who face difficulties accessing frequent in-person consultations. However, the actual benefits depend on whether the prediction is sufficiently accurate, whether follow-up services are available, and whether patients can access the recommended interventions.

Despite their potential, AI-based smart healthcare systems face several scientific, ethical, and operational challenges. Predictive models may perform well on the datasets used during development but produce less reliable results when applied to populations with different demographic characteristics, disease prevalence, healthcare practices, or access to medical services. Incomplete records, incorrect labels, measurement errors, and unrepresentative training data may introduce systematic bias. Aversano, L., Iammarino, M., Mancino, I., & Montano, D. (2024). Explained that Complex models can also be difficult for healthcare professionals and patients to interpret, creating uncertainty about the reasons behind

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
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particular predictions. Furthermore, sensitive health information requires strong protection against unauthorized access, misuse, and inappropriate disclosure. The integration of automated predictions into clinical practice also raises questions about professional accountability, informed consent, patient autonomy, and responsibility for errors. Consequently, further investigation is needed into how technical performance, fairness, interpretability, privacy, and practical clinical usefulness can be considered together rather than evaluated as separate concerns.This research examines AI-based smart healthcare systems for early disease prediction by reviewing the relevant technological approaches, healthcare applications, implementation challenges, and opportunities for future development. It focuses on literature published between 2023 and 2025 to reflect recent developments in AI-assisted healthcare and predictive analytics. The study seeks to explain how machine learning, deep learning, wearable monitoring, electronic health records, and clinical decision-support systems can contribute to earlier identification of disease risk. It also considers the importance of trustworthy AI, representative datasets, external validation, privacy protection, and human oversight. The significance of the research lies in its integrated perspective: the usefulness of a smart healthcare system cannot be determined by predictive accuracy alone, because the system must also be safe, understandable, accessible, and clinically actionable. By synthesizing these dimensions, the paper aims to provide a foundation for researchers, healthcare administrators, technology developers, and policymakers interested in developing responsible and effective predictive healthcare systems.

RESEARCH QUESTION

1. How can artificial intelligence-based smart healthcare systems improve the early prediction of diseases, and what technological, clinical, ethical, and operational factors influence their accuracy, reliability, and practical implementation?

RESEARCH OBJECTIVES

1. To examine the role of artificial intelligence, machine learning, and deep learning in early disease prediction.

LITERATURE REVIEW

These systems are designed not only to classify existing disease but also to estimate future risk, detect early warning signals, and support preventive interventions. The development of electronic health records has been especially important because longitudinal patient information enables researchers to investigate relationships between medical history, physiological measurements, diagnoses, and subsequent health outcomes. Nasarudin et al. (2024) review deep learning approaches and online healthcare databases for health prediction, highlighting the significance of electronic health records as a foundation for predictive modelling. El Morr, C., Ozdemir, D., Asdaah, Y., Saab, A., El-Lahib, Y., & Sokhn, E. S. (2024). Explains that This research direction demonstrates that smart healthcare depends on the coordinated use of data infrastructure, analytical models, and clinical processes rather than on the algorithm alone.The growing availability of computational resources has also enabled researchers to examine more complicated clinical problems. Traditional statistical

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
P-I-SSN: XXXXXXXXXX | E-I-SSN: XXXXXXXXXX

models remain useful for identifying associations and estimating risk, while modern machine learning approaches can represent nonlinear relationships among variables. Deep learning can learn complex features from medical images, time-series measurements, and other high-dimensional data. Nevertheless, more sophisticated models are not automatically superior in every clinical setting. Their usefulness depends on the size and representativeness of the training dataset, the relevance of the selected features, and the reliability of the outcomes used for model development. A meaningful evaluation must therefore consider whether the model offers an improvement over existing clinical assessment methods, not simply whether it performs well on a development dataset.

Machine learning is one of the principal technologies used in early disease prediction. Supervised learning algorithms are trained using examples in which clinical characteristics are associated with known outcomes. Common approaches include logistic regression, decision trees, random forests, support vector machines, gradient-boosting algorithms, and neural networks. These methods can be used to estimate the likelihood of diabetes, cardiovascular complications, kidney disease, and other medical conditions when suitable training data and clearly defined outcomes are available. Unsupervised learning methods, in contrast, identify patterns or groups within data without requiring every observation to have a predefined disease label. Such methods may help researchers discover patient subgroups with similar risk profiles, although the clinical meaning of the resulting groups requires further assessment.Al-Nafjan et al. (2025) examine AI applications in predictive healthcare, including predictive techniques, application areas, evaluation measures, and implementation challenges. Their systematic review reflects the increasing interest in using predictive analytics to support proactive care and personalized interventions. A key implication of this literature is that model selection should reflect the clinical problem. For example, an interpretable regression model may be appropriate when a healthcare team needs a transparent risk score, whereas a more complex model may be useful when nonlinear relationships or high-dimensional data are central to the prediction task. Sinnott, N. N. A. J. F. (2024). revealed that Regardless of the algorithm, predictive performance should be assessed using appropriate metrics and independent validation.Another important consideration is the distinction between risk prediction and diagnosis.

Deep learning is particularly relevant when healthcare information contains complex structures that are difficult to represent using manually selected variables. Convolutional neural networks are commonly associated with image analysis, while recurrent neural networks and other sequence-learning methods can model temporal patterns. Transformer-based architectures can process sequences and relationships within large datasets, including selected forms of clinical text and longitudinal health information. These techniques provide opportunities to analyze radiological images, pathology specimens, physiological signals, and patient records. Their potential contribution to early prediction lies in the ability to detect subtle combinations of features that may be associated with disease onset or progression.Nasarudin et al. (2024) describe developments in deep learning-based prediction using electronic health records and discuss the different ways such data can be represented and analyzed. However, clinical records contain characteristics that make predictive modelling challenging. Measurements may be recorded at irregular intervals, patients may have different numbers of visits, and the absence of a test result may itself reflect clinical decisions rather than random missingness. A model that does not account for these properties may learn misleading patterns. Researchers must also guard against data leakage, in which

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
P-I-SSN: XXXXXXXXXX | E-I-SSN: XXXXXXXXXX

information that would not have been available at the intended prediction time inadvertently enters model development.

Wearable devices, connected sensors, and mobile health applications are expanding the range of information available for disease prediction. Depending on the device, these technologies can collect heart rate, physical activity, sleep duration, oxygen saturation, temperature, and other physiological measurements. Unlike isolated clinical tests, repeated measurements can help reveal changes over time. Saad, H. S., Zaki, J. F., & Abdelsalam, M. M. (2025). Elaborated on An AI model may use such changes to flag unusual patterns, estimate health risks, or recommend that a patient seek further assessment. This approach may be especially valuable for remote monitoring, chronic disease management, and populations that cannot attend frequent hospital visits.Aversano et al. (2024) systematically review AI approaches for smart health devices and discuss the relevance of AI methods to data collected through connected health technologies. Saad, Zaki, and Abdelsalam (2024) also examine the use of machine learning and wearable devices, emphasizing the tasks and challenges associated with intelligent health monitoring. Taken together, this literature highlights the importance of matching the analytical technique to the type of sensor data and the intended clinical purpose.However, continuous monitoring does not necessarily guarantee accurate early prediction. Wearable measurements can be affected by motion, device placement, battery limitations, inconsistent wearing habits, and differences between device manufacturers. In addition, consumer devices may not provide measurements that are sufficiently reliable for a particular clinical decision. False alerts can create anxiety and increase demand for unnecessary consultations, while missed alerts can create a false sense of security. Therefore, smart monitoring systems should specify their intended use, establish thresholds through suitable clinical evaluation, and explain how users should respond to alerts. Continuous monitoring is most useful when supported by clear follow-up procedures and access to qualified healthcare professionals.

Models trained on longitudinal records can investigate how patient characteristics change before an outcome occurs. When combined with information from imaging systems, wearable devices, and laboratory testing, these records can potentially support a more comprehensive assessment of health risk. Such integration is often described as multimodal prediction because different types of information are processed together to produce a risk estimate or classification.The review by Nasarudin et al. (2024) provides a relevant foundation for understanding predictive modelling using electronic health records and online healthcare databases. More recent work on predictive modelling with electronic health records also emphasizes the methodological challenges posed by the structure and variability of clinical data. Wang, J., Luo, J., Ye, M., Wang, X., Zhong, Y., Chang, A., ... & Ma, F. (2024, August). Explains that These issues include inconsistent coding systems, different documentation practices, incomplete observations, and variations in the timing of measurements.Multimodal integration can improve the amount of information available to a model, but it can also increase technical complexity. Information from different sources may use different units, timestamps, formats, and levels of reliability. The absence of one modality may be common in some patient groups, making the model less useful in practice. Researchers must therefore determine whether combining data sources offers meaningful improvement over simpler models, and whether the benefits justify the cost of collecting, integrating, and maintaining the additional information. Secure interoperability standards and consistent data definitions are important for enabling different healthcare systems to exchange information reliably.

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
P-I-SSN: XXXXXXXXXX | E-I-SSN: XXXXXXXXXX

The interpretability of predictive models is a central concern in healthcare because clinicians need to understand the limitations of a prediction and decide how it should influence patient care. Explainable AI (XAI) includes methods intended to clarify the factors contributing to a model's output. Techniques such as feature importance, SHAP values, and local surrogate explanations can help indicate which variables influenced a particular prediction. These approaches may support clinical review, model debugging, and communication between technical developers and healthcare professionals. Nevertheless, an explanation generated by a model should not automatically be interpreted as proof of causation or as a complete representation of the biological processes underlying a disease.Albahri et al. (2023) review trustworthy and explainable AI in healthcare, addressing model quality, bias, and the fusion of different data sources. A 2024 survey of explainable AI in healthcare similarly discusses the relationship between interpretability, clinical workflows, technical performance, and regulatory expectations. This body of research suggests that transparency should be incorporated into the design and evaluation of predictive systems rather than added as an afterthought.Trustworthiness also depends on factors beyond interpretability. A model must be adequately validated, securely managed, monitored after deployment, and evaluated for performance across relevant patient groups.

METHODOLOGY

The proposed study adopts a structured literature-based methodology to investigate the role of artificial intelligence in smart healthcare systems for early disease prediction. A literature-based approach is appropriate because the research focuses on synthesizing existing knowledge, comparing technological approaches, identifying recurring implementation challenges, and developing a conceptual understanding of how predictive healthcare systems operate. The review covers research published from January 2023 to December 2025, with emphasis on peer-reviewed journal articles, systematic reviews, relevant technical studies, and authoritative healthcare guidance. The principal topics include machine learning, deep learning, electronic health records, wearable health devices, clinical decision-support systems, disease-risk prediction, explainable AI, data privacy, and clinical validation. Literature searches should be conducted using databases such as PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar, with search terms including “artificial intelligence in healthcare,” “early disease prediction,” “smart healthcare systems,” “machine learning for disease prediction,” “AI-based health monitoring,” “electronic health records predictive modelling,” “wearable devices and healthcare,” and “explainable AI in medicine.” Boolean operators such as AND and OR can be used to combine related concepts and improve search precision.The selection of literature should follow predefined inclusion and exclusion criteria to improve transparency and reduce the risk of selective interpretation. Studies should be included when they were published within the specified period, addressed AI applications relevant to disease prediction or smart healthcare, and provided sufficient information about their methods, applications, findings, or implementation implications. Systematic reviews, empirical studies, methodological papers, and authoritative guidelines may all be considered, provided that their relevance to the research question is clear.

RESEARCH DESIGN

This study uses a descriptive, analytical, and thematic research design to examine AI-based smart healthcare systems for early disease prediction. The descriptive component explains the

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
P-I-SSN: XXXXXXXXXX | E-I-SSN: XXXXXXXXXX

main technologies, data sources, clinical applications, and predictive approaches discussed in recent literature. The analytical component compares the reported advantages, limitations, and implementation requirements of different approaches. The thematic component organizes the evidence into recurring areas, including prediction accuracy, early risk identification, continuous monitoring, multimodal data integration, model interpretability, algorithmic fairness, privacy, and clinical usability. The study is cross-sectional in the sense that it synthesizes a defined body of literature from the 2023–2025 publication period rather than following patients or healthcare systems prospectively. Its unit of analysis is the relevant publication or documented research contribution, not an individual patient. This design is suitable for identifying patterns across a diverse research field without incorrectly implying that the paper has generated new clinical outcome data.The conceptual framework underlying the research proposes that the effectiveness of an AI-based smart healthcare system is influenced by the interaction of five major components. These components are interdependent: even a technically accurate algorithm may provide limited benefit if its data are unrepresentative, its alerts are poorly integrated, or healthcare professionals cannot act on its predictions.The research design also distinguishes between technical outcomes and clinical outcomes. Technical outcomes include discrimination, sensitivity, specificity, calibration, and performance across patient subgroups. Clinical and operational outcomes include timely identification of at-risk patients, appropriate referral, clinician acceptance, patient safety, and the feasibility of using the system in routine care. This distinction prevents the study from treating a high statistical performance score as sufficient proof of practical benefit.

DATA ANALYSIS

The data analysis for this study is based on qualitative thematic synthesis of the selected literature rather than statistical analysis of newly collected patient-level observations. Each publication should be examined to identify its main research objective, type of disease or clinical task, AI technique, source of healthcare data, validation approach, reported benefits, limitations, and recommendations. These extracted characteristics should be organized into a structured evidence matrix to make similarities and differences easier to identify. The initial analysis should classify studies by technological approach, such as conventional machine learning, deep learning, wearable-based monitoring, electronic health record modelling, multimodal prediction, and explainable AI. A second level of analysis should examine clinical applications, including cardiovascular disease, diabetes, cancer, neurological conditions, chronic disease management, and population-level outbreak prediction. A third level should classify implementation issues, including data quality, privacy, fairness, interpretability, clinical integration, and ongoing model monitoring. This multi-level structure helps connect technical developments with the clinical problems they are intended to address.The comparative analysis should examine the strengths and limitations of the principal AI approaches. Conventional machine learning models may be advantageous when structured clinical data are available and transparent risk estimates are important. Tree-based methods can represent nonlinear relationships and interactions, while regression models may provide useful baselines and interpretable associations. Deep learning approaches may be more suitable for complex images, time-series data, or large and heterogeneous datasets, but their performance can depend heavily on data volume, preprocessing, and careful validation. Wearable-based systems offer the possibility of repeated measurement and remote

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
P-I-SSN: XXXXXXXXXX | E-I-SSN: XXXXXXXXXX

monitoring, although the reliability of their predictions depends on sensor quality, user adherence, and the relevance of the measured signals.

FINDINGS

The literature reviewed for this paper indicates that AI-based smart healthcare systems offer several potential pathways for improving early disease prediction, although their actual effectiveness depends on the clinical setting and quality of implementation. One major theme is the ability of machine learning to identify relationships among multiple clinical variables and estimate disease risk before conventional symptoms become prominent. Predictive modelling can help clinicians prioritize patients for screening, follow-up, or further investigation. Deep learning expands these possibilities by processing complex inputs, including medical images, physiological signals, and longitudinal records. However, the literature also indicates that the complexity of an algorithm does not guarantee superior performance. Model selection should reflect the characteristics of the available data, the prediction task, and the requirements of the intended clinical workflow.A second theme is the potential value of continuous health monitoring. Wearable devices and connected sensors can provide repeated measurements that may reveal changes not captured during occasional medical consultations. When these measurements are analyzed alongside medical history and other clinical information, they may support more personalized risk assessment and remote monitoring. This capability could be useful for chronic disease management and for identifying individuals who need further evaluation. Nevertheless, continuous data collection creates additional challenges involving device reliability, missing measurements, false alarms, patient adherence, and the interpretation of abnormal readings. A clinically useful system must therefore include procedures for reviewing alerts, confirming suspected problems, and directing patients toward appropriate care.A third theme is the importance of data integration. Electronic health records provide longitudinal clinical context, while imaging systems, laboratory tests, and wearable devices contribute different types of information.

CONCLUSION

Artificial intelligence-based smart healthcare systems represent an important development in the transition from reactive medical treatment toward proactive, preventive, and personalized healthcare. This research has examined how machine learning, deep learning, electronic health records, wearable devices, connected sensors, and clinical decision-support systems can contribute to the early prediction of diseases. The reviewed literature indicates that AI can support the identification of disease-related patterns, estimation of individual risk, continuous monitoring, and prioritization of patients for further assessment. These capabilities may be valuable in the management of cardiovascular diseases, diabetes, cancer, neurological disorders, and other conditions in which timely identification can influence subsequent care. By processing complex information and detecting patterns across different data sources, predictive systems may provide healthcare professionals with additional information to support clinical decision-making. However, the effectiveness of these applications depends on the reliability of the underlying data, the suitability of the predictive model, and the availability of appropriate clinical interventions.The study also highlights that the successful adoption of AI requires more than technical accuracy. Data quality, algorithmic fairness, explainability, privacy protection, cybersecurity, and clinical validation

International Journal Of
Artificial Intelligence And
Engineering Innovation
VOL 01 | No. 1 | 2026
P-I-SSN: XXXXXXXXXX | E-I-SSN: XXXXXXXXXX

are essential considerations throughout the development and deployment process. Models trained on limited or unrepresentative datasets may perform inconsistently across populations, while poorly calibrated predictions can lead to unnecessary investigations or missed opportunities for early intervention. Similarly, wearable monitoring and automated alerts cannot deliver their full potential unless healthcare professionals have clear procedures for interpreting and responding to the information generated.

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