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RESEARCH ARTICLE

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THE IMPACT OF ARTIFICIAL INTELLIGENCE IN IMPROVING THE DIAGNOSIS AND TREATMENT OF CHRONIC DISEASES

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ABSTRACT

Background: AI is being used more in healthcare to help diagnose and treat chronic diseases by looking at large sets of clinical data and making decisions for doctors. Its real-world effects, on the other hand, depend on how well it is used and built into health systems. **Aim;** The point of this study was to look at how AI can help diagnose and treat chronic diseases better and to find the technological, infrastructure, and policy factors that affect how well it works for doctors. **Methodology:** A structured questionnaire was sent to a group of healthcare professionals as part of a descriptive–correlational design. The test had three parts: using AI for diagnosis and treatment, putting it all together and managing it, and looking at clinical and patient outcomes and workflow. SPSS was used to look at the data. It did tests for validity and reliability, descriptive statistics, Pearson correlations, and multiple regression. **Results:** Overall, Cronbach's alpha = 0.929 showed that the scale was very reliable. A strong link existed between AI use and outcomes ($r = 0.672$, $p < 0.001$), as well as between implementation/governance and outcomes ($r = 0.659$, $p < 0.001$). We found that using AI ($\beta = 0.426$, $p < 0.001$) and putting it into practice and making sure it's governed ($\beta = 0.414$, $p < 0.001$) together explained 55.6% of the differences in clinical and patient outcomes. **Conclusion:** When the right infrastructure, interoperability, governance, and professional acceptance are in place, AI can make diagnosis, treatment, and workflow a lot better in managing chronic diseases. **Recommendations:** Health systems should put money into digital infrastructure that can work with other systems, clear rules and regulations, training for staff, and AI tools that are easy to understand and focus on the needs of patients. In the future, researchers should look into disease-specific, longitudinal, and cost-effectiveness outcomes.

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INTRODUCTION

1.1 Introduction and Background: Heart diseases, diabetes, liver diseases, and breathing problems that don't go away are just a few of the chronic diseases that affect people around the world (Xie et al., 2021; Decharatanachart et al., 2021). About 71% of all deaths in the world are caused by these diseases, according to the World Health Organization (Rashid et al., 2022). This shows how widespread their effects are on economies and healthcare systems. Chronic diseases are hard to manage because they need to be watched over all the time, treated quickly, and patients need to be involved for a long time (Yu et al., 2022; Pan et al., 2021). Against this backdrop, artificial intelligence (AI) has emerged as a revolutionary tool capable of transforming chronic disease diagnosis and management (Arefin, 2024). Early AI systems were mostly based on rules and were made to copy very specific decision-making algorithms. AI has grown over time to include advanced deep learning, machine learning, and natural language processing techniques that can look at big, complicated

datasets like patient demographics, clinical test results, and sensor outputs from wearable tech (Singareddy et al., 2023; Xie et al., 2021). These new technologies make predictive analytics possible, which can find small patterns in disease that are missed by traditional methods (Rashid et al., 2022). To give you an example, Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) are very good at finding early signs of heart disease, diabetes, and liver fibrosis (Decharatanachart et al., 2021).

1.2 Statement of the Problem: Even though there is some good evidence that AI can help find chronic diseases earlier and make treatments more effective (Singareddy et al., 2023; Decharatanachart et al., 2021), it isn't always used properly in the real world. Many healthcare facilities don't have an integrated infrastructure, which means that providers can't combine patient data from different sources into AI systems (Pan et al., 2025). Also, AI development is fragmented, with many platforms and models working in separate

environments. This makes it harder to have a big effect and get a lot of people to use AI (Subramanian *et al.*, 2020).

Core Issue: There isn't a standard, evidence-based way to add AI to the steps of managing chronic diseases, especially in healthcare settings that aren't all the same and have different resources (Xie *et al.*, 2021). To make matters worse, healthcare professionals are still having a hard time with limited interoperability, inconsistent data quality, and not enough regulatory frameworks for okaying AI-driven clinical decisions (Arefin, 2024; Emeihe *et al.*, 2024).

1.3 Research Objectives

1. To evaluate the effectiveness of AI-enhanced diagnostic tools and interventions in chronic disease management, focusing on early detection, improved diagnostic accuracy, and treatment outcomes.
2. To identify the key technological, infrastructural, and regulatory factors that facilitate or hinder the adoption of AI-based approaches in mainstream healthcare systems.
3. To investigate how AI-driven platforms and applications impact patient engagement, adherence to treatment plans, and overall quality of life in diverse chronic disease populations.

1.4 Research Questions

Primary Research Question

- What factors influence the process of using artificial intelligence to improve and diagnose the treatment of chronic diseases?

Sub-Questions

- What technological, infrastructural, and regulatory barriers or enablers affect large-scale implementation?
- How do AI-enhanced tools influence patient engagement, adherence, and quality of life?

2: LITERATURE REVIEW

2.1 Introduction

In the last few decades, technological advances, especially in the field of artificial intelligence (AI), have caused huge changes in the health sector. Chronic diseases like heart disease, diabetes, liver problems, chronic obstructive pulmonary disease (COPD), and others that don't go away are very bad for people's health, society, and the economy (Rashid *et al.*, 2022; Xie *et al.*, 2021). The WHO says that chronic diseases cause about 71% of all deaths in the world. This shows how important it is to improve early detection, diagnosis, and long-term disease management (Decharatanachart *et al.*, 2021; Singareddy *et al.*, 2023). In this situation, AI stands out because it has the potential to solve some of the biggest problems in managing chronic diseases, such as a lack of clinical resources, broken up patient data, and wrong diagnoses (Subramanian *et al.*, 2020). It includes predictive algorithms that use huge clinical datasets and complex machine learning (ML) models that find disease patterns that are invisible to the naked eye (Pan *et al.*, 2025) using AI. The existing literature in this chapter is looked at to see how AI innovations are changing the way chronic diseases are treated, making it possible for earlier detection, more accurate treatment, and more involved patients (Yu *et al.*, 2022; Arefin, 2024). As computer hardware, big data analytics, cloud technologies, and wearable sensors have all improved at the same time, so has AI for healthcare applications (Emeih *et al.*, 2024; Xie *et al.*, 2021). AI-based methods are now being used more in clinical settings, such as in remote monitoring platforms, AI-assisted image analysis, chatbots for patient self-management, and knowledge graphs that bring together different data sources (Rashid *et al.*, 2022). Even so, there are still big gaps. Many AI projects are still in the testing phase because electronic health record (EHR) systems don't talk to each other well enough, there are ethical concerns about how

fair algorithms are, and there aren't any standard ways for people to share data (Pan *et al.*, 2021; Subramanian *et al.*, 2020). The first part of this chapter talks about the ideas behind using AI to help manage chronic diseases and describes how complicated these conditions are. After giving a brief history of AI's uses in healthcare, it goes on to look at some of the most well-known AI methods and how they can be used in real life, covering everything from early detection to personalized treatment. This chapter brings together comparative insights from several studies to show the problems and trade-offs that happen in the real world. It also talks about ongoing problems like algorithmic bias and regulatory hurdles, and it points out important gaps. This sets the stage for the current study's goal to come up with more comprehensive and effective solutions for places where people have chronic diseases (Decharatanachart *et al.*, 2021).

2.2 Conceptual Framework: AI in Chronic Disease Management

Chronic diseases often develop with few or mild symptoms, making early diagnosis difficult (Singareddy *et al.*, 2023). Unlike acute conditions, they may persist for years or throughout life and require continuous monitoring, long-term treatment, lifestyle changes, and regular follow-ups (Rashid *et al.*, 2022). Their multifactorial causes and frequent comorbidities, such as hypertension and kidney disease in diabetes, complicate diagnosis, medication management, and treatment decisions (Decharatanachart *et al.*, 2021). AI-based solutions can integrate diverse datasets, including genomic, imaging, laboratory, and wearable sensor data, to identify disease patterns and predict progression. These capabilities support personalized treatment and improved clinical decision-making (Yu & Zhang, 2022). AI applications in chronic disease care began primarily with expert systems in the 1980s and 1990s, using expert-defined knowledge bases and fixed if-then rules, but their limited adaptability reduced their effectiveness in complex cases (Singareddy *et al.*, 2023; Subramanian *et al.*, 2020). During the 2000s, advances in computing and digital health data enabled machine learning methods, including decision trees, random forests, and SVMs, to identify patterns and predict chronic disease risks from electronic health records (Xie *et al.*, 2021; Pan *et al.*, 2025). In the 2010s, deep learning improved diagnostic capabilities, particularly through CNNs for medical imaging and RNNs for time-series data (Arefin, 2024; Decharatanachart *et al.*, 2021). Knowledge graphs further integrated clinical guidelines and patient data (Yu & Zhang, 2022). However, adoption remains challenging due to interoperability, regulatory, and infrastructure barriers (Emeih *et al.*, 2024).

2.3 Key AI Techniques and Methodologies

"Artificial intelligence" (Pan *et al.*, 2025) is a broad term for a set of computer techniques that allow machines to copy, improve, or go beyond human cognitive functions. There are many subfields in healthcare that meet different needs: AI technologies provide diverse approaches for chronic disease management. Machine learning includes supervised methods, such as random forests, SVMs, ensemble models, and logistic regression, which predict disease risk, while unsupervised learning identifies hidden patterns and patient groups (Rashid *et al.*, 2022; Decharatanachart *et al.*, 2021). Deep learning methods, particularly CNNs, support medical image analysis, while RNNs and LSTM networks process time-series data such as glucose levels and vital signs (Xie *et al.*, 2021; Subramanian *et al.*, 2020). Knowledge graphs integrate patient records and clinical guidelines, improving understanding of relationships between medical information and supporting clinical decisions (Yu & Zhang, 2022). NLP extracts valuable information from unstructured clinical and social media text and enables AI chatbots for patient support (Noel *et al.*, 2023). Predictive analytics and ensemble methods improve disease-risk prediction by combining multiple data sources (Arefin, 2024). IoT integration enables continuous monitoring through wearable and smart devices and provides real-time alerts for abnormal health changes (Emeih *et al.*, 2024).

2.4 AI Applications for Early Detection of Chronic Diseases:

Cardiovascular diseases remain leading causes of global mortality, highlighting the need for faster and more accurate risk assessment (Subramanian *et al.*, 2020). Traditional tools such as the Framingham

Risk Score may overlook complex interactions among genetic, environmental, and lifestyle factors (Arefin, 2024). AI-based risk stratification integrates clinical, imaging, biomarker, and social data to identify hidden high-risk patterns (Rashid *et al.*, 2022), while CNNs can detect early cardiac structural changes (Singareddy *et al.*, 2023). Wearables and ECG devices enable continuous monitoring and early detection of arrhythmias such as AFib (Pan *et al.*, 2025), with smartphone integration supporting patient engagement (Yu & Zhang, 2022). AI platforms have also improved arrhythmia detection and accelerated diagnosis through knowledge-graph analytics (Obermeyer & Emanuel, 2016; Xie *et al.*, 2021).

AI technologies support the management of diabetes, chronic liver diseases, and respiratory conditions through prediction, monitoring, and personalized interventions. For type 2 diabetes, machine learning models identify early risk using laboratory results, lifestyle factors, BMI, and glucose-monitoring data (Decharatanachart *et al.*, 2021; Arefin, 2024). Continuous glucose monitoring combined with AI can predict hypo- and hyperglycemia and provide real-time alerts (Singareddy *et al.*, 2023; Subramanian *et al.*, 2020). AI chatbots also encourage personalized dietary and exercise changes, improving metabolic control (Rashid *et al.*, 2022; Yu & Zhang, 2022). In chronic liver disease, AI-assisted imaging reduces reliance on invasive biopsies, while machine learning integrates biochemical and genomic data to improve diagnosis and risk stratification (Decharatanachart *et al.*, 2021; Pan *et al.*, 2025; Subramanian *et al.*, 2020). AI can identify patients at high risk of cancer or fibrosis progression (Xie *et al.*, 2021). For respiratory diseases, AI-enabled spirometry, connected inhalers, and telemonitoring predict exacerbations, support disease phenotyping, and reduce hospital utilization (Singareddy *et al.*, 2023; Yu & Zhang, 2022; Pan *et al.*, 2025; Subramanian *et al.*, 2020).

2.5 AI for Personalized Treatment and Decision Support: AI plays an important role in precision medicine by integrating genetic, phenotypic, environmental, imaging, omics, and EHR data to improve risk assessment and treatment selection (Subramanian *et al.*, 2020). Applications include pharmacogenomics, targeted therapies, and potential AI-guided gene editing (Pan *et al.*, 2025; Yu & Zhang, 2022; Decharatanachart *et al.*, 2021). Clinical decision support systems (CDSS) provide evidence-based recommendations, improve medication management and diagnostic accuracy, and facilitate care coordination (Arefin, 2024; Subramanian *et al.*, 2020; Singareddy *et al.*, 2023; Yu & Zhang, 2022; Rashid *et al.*, 2022). However, alert fatigue and limited understanding of AI outputs remain concerns, highlighting the importance of explainable AI and user-friendly systems (Emeihe *et al.*, 2024). AI-powered virtual coaching further supports self-management through personalized dietary guidance, exercise tracking, and stress management (Pan *et al.*, 2025; Singareddy *et al.*, 2023; Decharatanachart *et al.*, 2021; Arefin, 2024). Evidence indicates that such interventions can improve clinical outcomes and encourage sustainable behavioral changes (Yu & Zhang, 2022).

2.6 Integrating AI, Wearable Technology, and Blockchain: AI-enhanced wearable technologies enable continuous monitoring of physiological data, helping detect early abnormalities that may be missed during periodic clinical visits (Xie *et al.*, 2021). AI analytics can identify tachycardia, arrhythmias, and sudden blood-pressure changes (Rashid *et al.*, 2022). Applications include monitoring fluid retention in heart failure, predicting glucose fluctuations in diabetes, and detecting respiratory deterioration through wearable oximeters (Decharatanachart *et al.*, 2021; Singareddy *et al.*, 2023; Yu & Zhang, 2022). Blockchain can further strengthen healthcare data security, privacy, integrity, and interoperability by securely integrating information from hospitals, telemedicine, laboratories, and wearable devices (Xie *et al.*, 2021). Combined with AI, blockchain and smart contracts can support patient-controlled data sharing and consent management while reducing unauthorized access or data modification (Emeihe *et al.*, 2024; Pan *et al.*, 2025).

2.7 Telemedicine, Remote Monitoring, and AI-Driven Platforms: AI-enabled telemedicine can improve healthcare equity by providing remote diagnosis and consultations for underserved and rural populations, reducing delays in accessing specialists and diagnostic services (Emeihe *et al.*, 2024; Decharatanachart *et al.*, 2021). AI-based image analysis, ECG interpretation, and symptom-tracking applications can reduce travel costs and waiting times while improving patient satisfaction (Rashid *et al.*, 2022). Portable devices can also allow local healthcare workers to collect patient data for AI-assisted preliminary assessments (Singareddy *et al.*, 2023). Remote monitoring systems provide real-time alerts for conditions such as heart failure and respiratory deterioration, enabling timely interventions and potentially reducing hospitalizations and healthcare costs (Yu & Zhang, 2022; Subramanian *et al.*, 2020). Furthermore, telemedicine platforms support patient empowerment through medication reminders, lifestyle tracking, appointment management, and data sharing (Pan *et al.*, 2025; Arefin, 2024). However, limited digital literacy, smartphone access, and internet connectivity can widen the digital divide and restrict adoption among disadvantaged populations (Emeihe *et al.*, 2024).

2.8 Comparative Analysis of Previous Research: AI-driven methods demonstrate strong potential for improving chronic disease diagnosis and prediction, with some models achieving high accuracy compared with traditional approaches (Rashid *et al.*, 2022). Machine learning can identify subtle risk patterns, although large-scale studies may reveal limitations in data quality and generalizability (Subramanian *et al.*, 2020; Decharatanachart *et al.*, 2021). Despite promising results, integrating AI into clinical environments remains challenging because of outdated EHR systems, workflow changes, and limited interoperability (Pan *et al.*, 2025; Singareddy *et al.*, 2023; Yu & Zhang, 2022). Standards such as FHIR aim to improve data exchange, but adoption remains inconsistent (Emeihe *et al.*, 2024). Ethical concerns include privacy, informed consent, algorithmic bias, and unclear liability for AI-related decisions (Decharatanachart *et al.*, 2021; Subramanian *et al.*, 2020; Singareddy *et al.*, 2023; Obermeyer & Emanuel, 2016; Yu *et al.*, 2022). Trust is also an important factor in the acceptance and continued use of technology. The trust model proposed by (Sharfi *et al.*, 2016) demonstrates the relevance of trust in shaping consumers' intentions to use technology, providing a useful conceptual basis for examining trust in AI-enabled healthcare systems. In the context of chronic disease management, establishing trust through transparency, reliability, understandable recommendations, and appropriate safeguards may therefore contribute to greater acceptance of AI by patients and healthcare professionals. AI can also improve patient engagement and clinical outcomes, although maintaining long-term participation remains difficult (Arefin, 2024; Rashid *et al.*, 2022; Pan *et al.*, 2025).

2.9 Challenges, Trade-Offs, and Gaps in the Literature: The implementation of AI in chronic disease management faces several challenges. Poor data quality, missing information, and inconsistent standards can reduce model reliability (Subramanian *et al.*, 2020). High infrastructure, cloud, and technical costs may limit adoption, particularly in developing countries (Singareddy *et al.*, 2023). The lack of model interpretability can also reduce clinical trust, although Explainable AI aims to address this limitation (Xie *et al.*, 2021; Arefin, 2024). Differences in regulatory requirements create additional barriers to implementation (Yu & Zhang, 2022). Furthermore, many AI solutions remain limited to small pilot studies, requiring large-scale validation (Rashid *et al.*, 2022; Pan *et al.*, 2025). Limited digital literacy may also restrict patient participation and access to AI-enabled healthcare services (Decharatanachart *et al.*, 2021; Emeihe *et al.*, 2024).

2.10 Conclusion

Research indicates that AI can transform chronic disease management by improving screening, diagnosis, patient engagement, and personalized treatment (Arefin, 2024; Decharatanachart *et al.*, 2021). Machine learning supports early risk detection, deep learning enables advanced image analysis, and knowledge graphs integrate diverse

health data. Telemedicine, wearable technologies, and blockchain can also improve healthcare accessibility, particularly for remote and underserved populations (Xie *et al.*, 2021; Emeihe *et al.*, 2024). However, large-scale implementation faces challenges including fragmented data, limited interoperability, regulatory uncertainty, privacy concerns, and algorithmic bias (Subramanian *et al.*, 2020). Although pilot studies demonstrate clinical benefits, further validation across diverse populations and healthcare settings is required (Pan *et al.*, 2025). Cost, sustainability, and the digital divide also limit adoption. Therefore, the literature supports developing AI solutions that are integrative, validated, ethical, and patient-centered to address technological, infrastructural, and human factors in chronic disease management.

3: RESEARCH METHODOLOGY

3.1. Research Design: This study adopts a descriptive and correlational research design to examine the relationship between artificial intelligence (AI) use and outcomes in chronic disease management, including early diagnosis, treatment effectiveness, and patient engagement. The design is appropriate because the study observes existing variables without experimental manipulation or controlled interventions. The descriptive component will assess perceptions, experiences, patterns of AI use, and related outcomes in healthcare settings, while the correlational component will examine statistical relationships between AI use, diagnostic accuracy, treatment adherence, and patient satisfaction. The study follows a quantitative orientation, using numerical data and statistical analysis to test research hypotheses and support generalizable findings. Additionally, open-ended questions may be incorporated to provide qualitative insights into patients' and users' real-world experiences with AI technologies, complementing the quantitative results.

3.2. Research Sample: The study population will consist of healthcare professionals, data scientists, and medical administrators who have direct or indirect experience with AI-based technologies in clinical settings. Purposive sampling will be employed to select participants with relevant exposure to AI applications in chronic disease diagnosis and treatment, ensuring that collected data is appropriate to the research objectives. A total of 205 participants will be recruited from public and private healthcare facilities that use AI systems, including applications in medical imaging, remote monitoring, and clinical decision support. The study will seek diverse perspectives by including participants from different professional backgrounds, geographical locations, and academic institutions. Ethical safeguards will include informed consent, protection of privacy and personal data, voluntary participation, and the right to withdraw from the study at any time without penalty. All participants will give their informed consent, and strict ethical rules will be followed when it comes to privacy, consent, and data protection. The study will also make sure that no one is forced to take part, and people who do take part will be able to quit at any time without being punished.

3.3. Data Collection Method and Instruments: The primary data collection tool will be a structured electronic survey questionnaire designed to assess the effectiveness of AI in chronic disease management, technological and infrastructure challenges, and patient engagement with AI-based tools. The questionnaire will be written in English and divided into sections covering demographic characteristics, AI usage patterns, perceived effectiveness, and implementation barriers. Most questions will use a 5-point Likert scale, supplemented by selected open-ended questions to capture participants' views and concerns.

Before distribution, the questionnaire will undergo pilot testing with a small group of professionals to assess clarity, reliability, and apparent validity, with revisions made based on feedback. The final questionnaire will be distributed electronically through professional healthcare networks, mailing lists, and discussion boards, with paper copies available when internet access is limited. All collected data will be anonymized, securely stored, and accessible only to authorized research personnel.

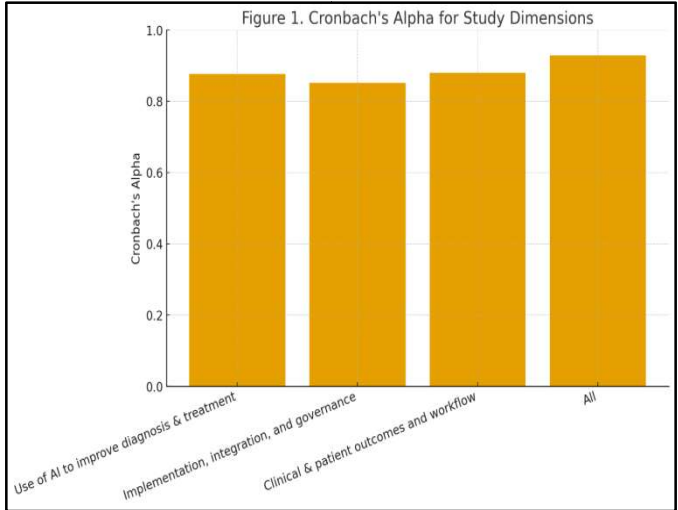
3.4. Data Analysis Procedure: Data will be analyzed using the Statistical Package for the Social Sciences (SPSS) after being organized, coded, and entered into the software. Descriptive statistics, including frequencies, percentages, means, and standard deviations, will be used to summarize participants' characteristics and identify patterns of AI use. Correlational analysis will examine relationships between key variables, such as AI utilization, diagnostic effectiveness, treatment outcomes, and patient adherence. Regression models may be applied to assess how independent variables, including AI tool type and professional experience, influence outcomes such as perceived treatment effectiveness and patient engagement. Where open-ended responses are collected, thematic content analysis will identify relevant themes and emerging insights. Results will be presented using tables and graphs and interpreted in relation to the research objectives and previous studies, with emphasis on transparency and reproducibility.

4: RESULTS AND DISCUSSION

4.1 Results Analysis, 4.1.1 Reliability
4.1.1.1 Table (1) Reliability analysis for research variables.

Variables	Cronbach's Alpha	Number of phares
Use of AI to improve diagnosis & treatment	0.877	5
Implementation, integration, and governance	0.852	5
Clinical & patient outcomes and workflow	0.880	5
All	0.929	15

The reliability analysis results, presented in the table above, demonstrate that research variables exhibit high internal consistency and reliability. With Cronbach's alpha of 0.929, the variable " **Clinical & patient outcomes and workflow** " shows the highest reliability with a Cronbach's alpha coefficient of 0.880, indicating strong internal consistency among the scale items. These findings confirm the accuracy and consistency of the data collected through the questionnaire, providing confidence in the research results.

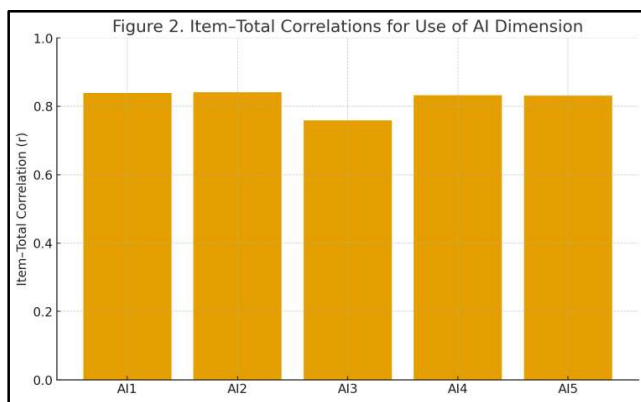


4.1.2 Validity

4.1.2.1 Table (2) Coefficient of correlation between the degrees of each statement of Use of AI to improve diagnosis & treatment

Statements	Pearson	Sig.
AI improves the accuracy and speed of chronic disease diagnosis	.839**	0.000
The availability of high-quality data enhances the effectiveness of AI applications in healthcare	.841**	0.000
The skills and experience of healthcare professionals influence how successfully AI is used in diagnosis and treatment	.759**	0.000
Interdisciplinary collaboration (eg, between clinicians, data scientists, and IT experts) strengthens AI outcomes in healthcare	.833**	0.000
The acceptance and trust of healthcare staff play a major role in integrating AI into daily medical practice	.832**	0.000

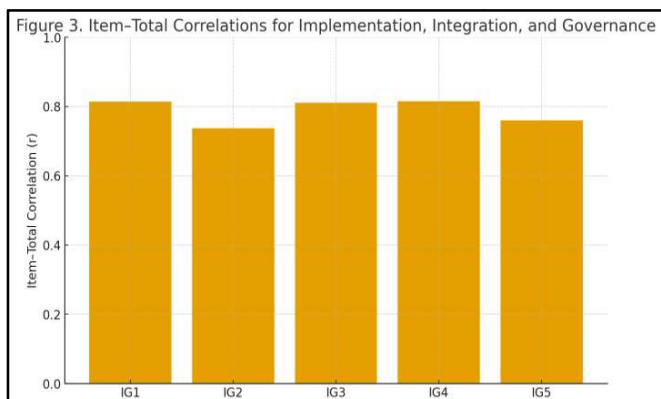
The table (2) shows that the correlation coefficients between each statement of (**Use of AI to improve diagnosis & treatment**), where the value of the correlation coefficient are between (0.759 – 0.841) which is a positive correlation.



4.1.2.2 Table (3) Coefficient of correlation between the degrees of each statement of Implementation, integration, and governance.

Statements	Pearson	Sig.
The technological infrastructure in healthcare facilities is sufficient to support AI systems	.814**	0.000
Data integration and interoperability issues hinder the effective deployment of AI	.737**	0.000
Cybersecurity and data privacy regulations are strong enough to protect patient information when using AI tools	.811**	0.000
Government policies and funding encourage innovation and adoption of AI in chronic disease management	.815**	0.000
The costs of AI implementation and maintenance limit its large-scale adoption in many healthcare settings	.760**	0.000

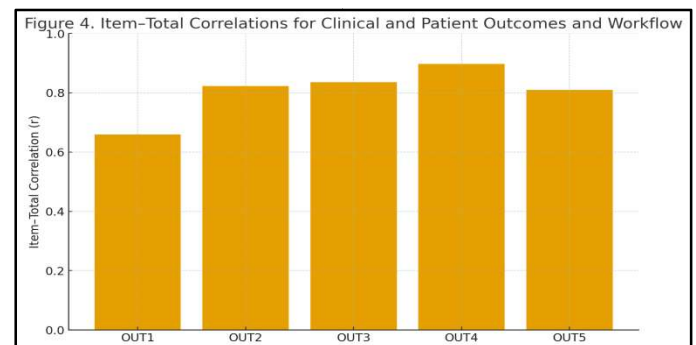
The table (3) shows that the correlation coefficients between each statement of (**Implementation, integration, and governance**), where the value of the correlation coefficient are between (0.737 – 0.815) which is a positive correlation.



4.1.2.3 Table (4) Coefficient of correlation between the degrees of each statement of Clinical & patient outcomes and workflow

Statements	Pearson	Sig.
AI applications help patients better understand and manage their chronic conditions	.659**	0.000
AI-supported communication platforms increase patient engagement with healthcare providers	.823**	0.000
The use of AI tools improves treatment adherence among chronic disease patients	.836**	0.000
AI contributes to enhancing patients' quality of life through personalized and proactive care	.897**	0.000
Patients generally trust AI-based recommendations in managing their health conditions	.810**	0.000

The table (4) shows that the correlation coefficients between each statement of (**Clinical & patient outcomes and workflow**), where the value of the correlation coefficient are between (0.659 – 0.897) which is a positive correlation.

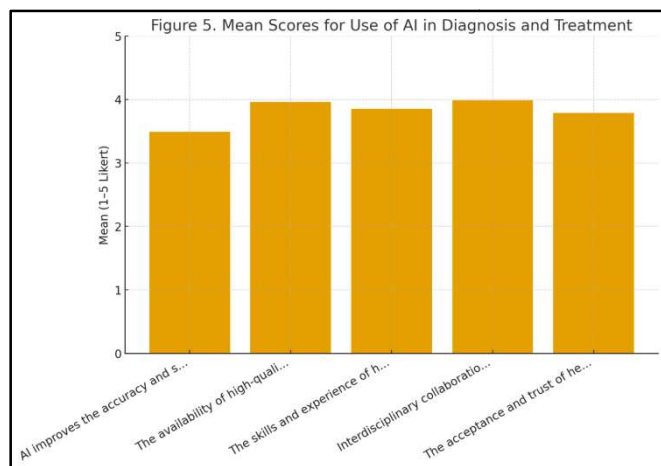


4.1.3 Descriptive Statistics:

4.1.3.1 Table (5) Descriptive Statistics of Use of AI to improve diagnosis & treatment.

N	Phrases	Mean	Std. Deviation	Rank
1	AI improves the accuracy and speed of chronic disease diagnosis	3.49	1.25	5
2	The availability of high-quality data enhances the effectiveness of AI applications in healthcare	3.96	1.06	2
3	The skills and experience of healthcare professionals influence how successfully AI is used in diagnosis and treatment	3.85	1.16	3
4	Interdisciplinary collaboration (eg, between clinicians, data scientists, and IT experts) strengthens AI outcomes in healthcare	3.99	1.09	1
5	The acceptance and trust of healthcare staff play a major role in integrating AI into daily medical practice	3.79	1.10	4
All		3.82	0.93	

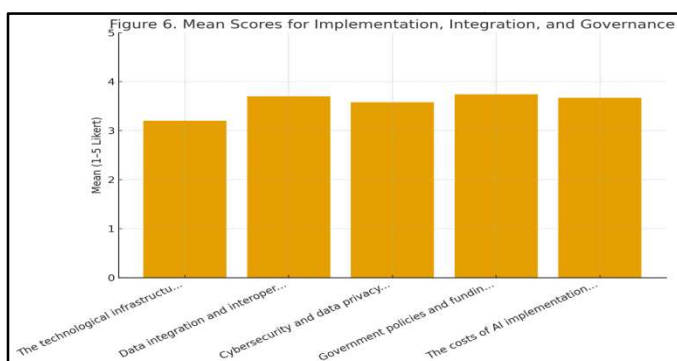
From the above table which describes the observations attitudes to Use of AI to improve diagnosis & treatment and we found that the average for all questions was 3.82 with standard deviation 0.93 and this reflects the high approval of observations on Use of AI to improve diagnosis & treatment, for the first rank the sentence of (Interdisciplinary collaboration (eg, between clinicians, data scientists, and IT experts) strengthens AI outcomes in healthcare.) came the first with average 3.99 and with standard deviation 1.09, for the sentence of (The availability of high-quality data enhances the effectiveness of AI applications in healthcare) came the second with average 3.96 and with standard deviation 1.06 and for the last sentence was (AI improves the accuracy and speed of chronic disease diagnosis) came the second with average 3.49 and with standard deviation 1.25.



4.1.3.2 Table (6) Descriptive Statistics of Implementation, integration, and governance

N	Phrases	Mean	Std. Deviation	Rank
1	The technological infrastructure in healthcare facilities is sufficient to support AI systems	3.20	1.26	5
2	Data integration and interoperability issues hinder the effective deployment of AI	3.70	1.03	2
3	Cybersecurity and data privacy regulations are strong enough to protect patient information when using AI tools	3.58	1.17	4
4	Government policies and funding encourage innovation and adoption of AI in chronic disease management	3.74	1.03	1
5	The costs of AI implementation and maintenance limit its large-scale adoption in many healthcare settings	3.67	1.09	3
All		3.58	0.89	

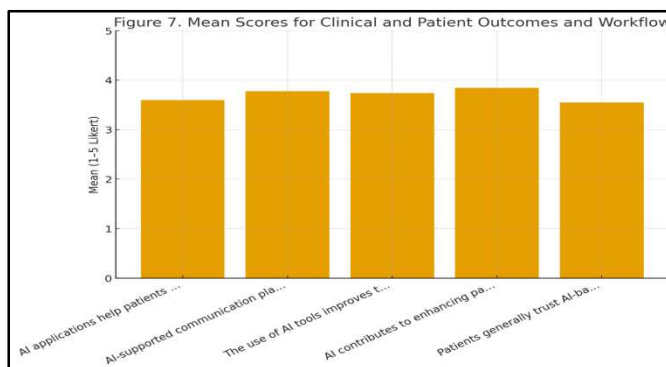
From the above table which describes the observations attitudes to Implementation, integration, and governance and we found that the average for all questions was 3.58 with standard deviation 0.89 and this reflects the high approval of observations on Social media advertising, for the first rank the sentence of (Government policies and funding encourage innovation and adoption of AI in chronic disease management.) came the first with average 3.74 and with standard deviation 1.03, for the sentence of (Data integration and interoperability issues hinder the effective deployment of AI) came the second with average 3.70 and with standard deviation 1.03 and for the last sentence was (The technological infrastructure in healthcare facilities is sufficient to support AI systems) with average 3.20 and with standard deviation 1.26.



4.1.3.3 Table (7) Descriptive Statistics of Clinical & patient outcomes and workflow

N	Phrases	Mean	Std. Deviation	Rank
1	AI applications help patients better understand and manage their chronic conditions	3.60	1.24	4
2	AI-supported communication platforms increase patient engagement with healthcare providers	3.78	1.13	2
3	The use of AI tools improves treatment adherence among chronic disease patients	3.74	1.08	3
4	AI contributes to enhancing patients' quality of life through personalized and proactive care	3.85	1.01	1
5	Patients generally trust AI-based recommendations in managing their health conditions	3.55	1.10	5
All		3.70	0.91	

From the above table which describes the observations attitudes to Clinical & patient outcomes and workflow and we found that the average for all questions was 3.70 with standard deviation 0.98 and this reflects the high approval of observations on Social media advertising, for the first rank the sentence of (Government policies and funding encourage innovation and adoption of AI in chronic disease management.) came the first with average 3.85 and with standard deviation 1.01, for the sentence of (AI-supported communication platforms increase patient engagement with healthcare providers) came the second with average 3.78 and with standard deviation 1.13 and for the last sentence was (Patients generally trust AI-based recommendations in managing their health conditions) with average 3.55 and with standard deviation 1.10.



4.1.4 Inferential Statistics:

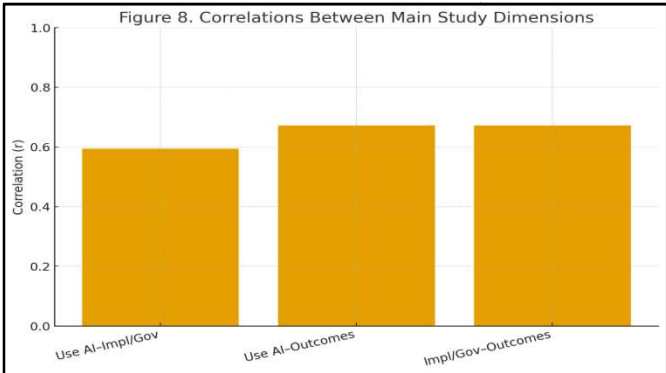
4.1.4.1 Table (8) Outputs of correlation Analysis to test the Impact of Artificial Intelligence in Improving the Diagnosis and Treatment of Chronic Diseases.

Correlations		Use of AI to improve diagnosis & treatment	Implementation, integration, and governance	Clinical & patient outcomes and workflow
Use of AI to improve diagnosis & treatment	Pearson Correlation	1	.594**	.672**
	Sig. (2-tailed)		.000	.000
	N	205	205	205
Implementation, integration, and governance	Pearson Correlation	.594**	1	.659**
	Sig. (2-tailed)	.000		.000
	N	205	205	205
Clinical & patient outcomes and workflow	Pearson Correlation	.672**	.659**	1
	Sig. (2-tailed)	.000	.000	
	N	205	205	205

** . Correlation is significant at the 0.01 level (2-tailed).

From the above table it is noticed that there is significant positive correlation between Use of AI to improve diagnosis & treatment and Implementation, integration, and governance with value 0.594 and

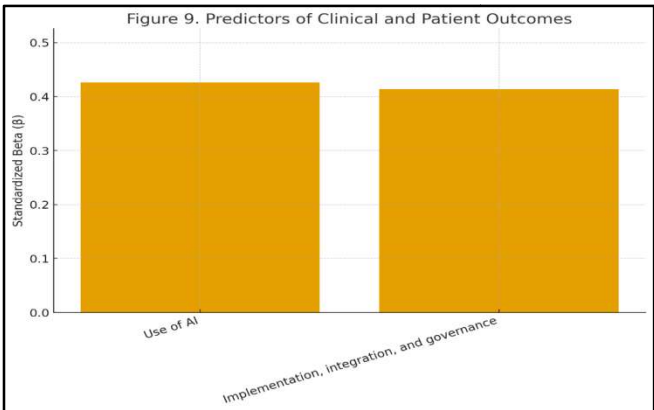
with sig 0.000 lower than 0.05, there is positive correlation between Use of AI to improve diagnosis & treatment and Clinical & patient outcomes and workflow with value 0.672 and with sig 0.000 lower than 0.05, there is positive correlation between Implementation, integration, and governance and Clinical & patient outcomes and workflow with value 0.659 and with sig 0.000 lower than 0.05.



4.1.4.2 Table (9) Outputs of Regression Analysis to test the Impact of Artificial Intelligence in Improving the Diagnosis and Treatment of Chronic Diseases.

R Square		F test statistics	
Clinical & patient outcomes and workflow	0.556	F	Significance
		126.651	0.000
		t test statistics	
	Beta (β)	T	Significance
Constant	0.095	2.967	0.003
Use of AI to improve diagnosis & treatment	0.426	7.442	0.000
Implementation, integration, and governance	0.414	6.903	0.000

From the above table it is noticed that Artificial Intelligence has positive significant effect on Improving the Diagnosis and Treatment of Chronic Diseases at $\alpha=0.05$.as the value of sig =0.000 lower than 0.05 and the value of R Square =0.556 means that the independent variable successes to interpret 56% of variation of the dependent variable.



4.1.5 RESULTS

After analyzing the data collected, we found that:

- For the questions of Use of AI to improve diagnosis & treatment and we found that the average for all questions was 3.82 with standard deviation of 0.93 and this reflects the high approval of observations on Use of AI to improve diagnosis & treatment.
- For the questions of Implementation, integration, and governance and we found that the average for all questions was 3.58 with a standard deviation of 0.89 and this reflects

the high approval of observations on Implementation, integration, and governance.

- For the questions of Clinical & patient outcomes and workflow and we found that the average for all questions was 3.70 with standard deviation 0.91 and this reflects the high approval of observations on Clinical & patient outcomes and workflow.
- From the above table it is noticed that there is significant positive correlation between Use of AI to improve diagnosis & treatment and Implementation, integration, and governance with value 0.594 and with sig 0.000 lower than 0.05, there is positive correlation between Use of AI to improve diagnosis & treatment and Clinical & patient outcomes and workflow with value 0.672 and with sig 0.000 lower than 0.05, there is positive correlation between Implementation, integration, and governance and Clinical & patient outcomes and workflow with value 0.659 and with sig 0.000 lower than 0.05.
- From the above table it is noticed that Artificial Intelligence has positive significant effect on Improving the Diagnosis and Treatment of Chronic Diseases at $\alpha=0.05$.as the value of sig =0.000 lower than 0.05 and the value of R Square =0.556 means that the independent variable successes to interpret 56% of variation of the dependent variable.

4.2 DISCUSSION

In this part, the empirical results of this study are put together with what we learned in Chapter Two. The discussion is based on the main ideas in the research questions, which are (1) how well AI can diagnose and treat chronic diseases, (2) how technological, infrastructure, and policy factors affect AI use, and (3) how AI affects patient engagement, treatment adherence, and quality of life. These themes show how the study's conceptual framework about the role of AI in managing chronic diseases is supported by the quantitative results.

4.2.1. Effectiveness of ai in diagnosis and treatment

The descriptive and inferential results strongly suggest that AI is seen as a useful tool by healthcare professionals for improving the diagnosis and treatment of long-term illnesses. The overall mean score for the "Use of AI to improve diagnosis and treatment" dimension was 3.82, which means that people generally liked how AI was used to improve diagnosis and treatment. With mean scores of 3.99 and 3.96, respondents especially agreed with statements that stressed the importance of working together across disciplines and using high-quality data. This shows that they understood that AI's effectiveness depends on both human expertise and strong data inputs. At the inferential level, the correlation analysis showed a strong positive relationship between the use of AI and clinical and patient outcomes and workflow ($r = 0.672$, $p < 0.001$). This means that more and better use of AI is linked to better clinical performance and results for patients. The regression results support this conclusion even more: the standardized beta coefficient for AI use ($\beta = 0.426$, $p < 0.001$) shows that this dimension makes a big and important contribution to explaining differences in clinical and patient outcomes. These results show that AI-powered tools, like decision-support systems, predictive models, and automated image analysis, are seen by practitioners as important ways to improve the quality and efficiency of managing chronic diseases. They are not just new technologies.

The research agrees with these real-world observations. Studies like Rashid *et al.* (2022) and Singareddy *et al.* (2023) have shown how AI can help doctors make more accurate diagnoses, find chronic diseases earlier, and make treatment plans more personalized. Their research shows that AI can handle a lot of clinical and imaging data, find subtle patterns that humans might miss, and give doctors recommendations based on solid evidence. The current study's results are similar to those of other studies in that they show that healthcare

professionals think AI can help with both diagnosis and ongoing treatment management. This is especially true when good data is used and clinical and technical experts work together. There is still some doubt among practitioners, though, as shown by the relatively lower (but still positive) mean for the item "AI improves accuracy and speed of diagnosis" (3.49). This level of detail is also shown in the research, which says that how well AI systems work in the real world depends on things like how representative the data is, how mature the system is, and how well AI outputs are integrated into clinical workflows. On the whole, though, these results support the idea that AI is a useful and growing tool for making better decisions about diagnosis and treatment in chronic disease care.

4.2.2. Technological, infrastructural, and governance factors

The second main theme is about the technological, infrastructure, and regulatory conditions that AI needs to work well in healthcare settings and stay that way. The overall mean for the dimension "Implementation, integration, and governance" was 3.58, which means that most people agree that these factors are important and that some progress has been made, but there are also some areas that need attention. Respondents gave statements about the role of government policies and funding pretty high marks (mean = 3.74), which shows that they think supportive policy frameworks and financial incentives encourage innovation and the use of AI in clinical settings. However, participants were worried about problems with data integration and interoperability (mean = 3.70) and weren't as sure that the current technology infrastructure is enough (mean = 3.20). These ideas show that there are still big gaps in technology and infrastructure, even though there may be policy signals that are helpful. The correlation analysis supports this view: there was a strong and positive link ($r = 0.659$, $p < 0.001$) between implementation, integration, governance, clinical and patient outcomes, and workflow. This suggests that better implementation strategies, systems that can work with each other, and strong governance structures are all linked to better clinical and patient outcomes.

The regression results show that these factors are even more important than we thought. The standardized beta coefficient for "Implementation, integration, and governance" ($\beta = 0.414$, $p < 0.001$) shows that this dimension has a strong effect on clinical and patient outcomes that is separate from direct AI use. It is almost as strong. This finding supports the idea that advanced AI tools can't guarantee better results on their own; instead, their success depends on an environment with the right infrastructure, clear governance mechanisms, good data management, and compliance with regulatory requirements. These ideas are very similar to what we read in Chapter Two, which talks about how interoperability, data privacy and security, ethical oversight, and the regulatory approval process are still hard. A lot of authors have said that inconsistent data standards and broken health information systems make it harder to use AI solutions in everyday care. Concerns about patient privacy, data protection, and algorithmic transparency make things even more complicated. This is why strong governance frameworks and clear regulatory guidance are needed. The results of this study back up these worries: the people who answered the survey know that policies and money can encourage innovation, but they also know that technological and infrastructure problems are still big problems. In this way, the study's results add to the ongoing debate that AI in healthcare needs to be looked at through a sociotechnical lens, which means that technological capabilities, organizational structures, and governance arrangements are all connected. Effective implementation, integration, and governance are not extras that can be added on, they are necessary for AI to have the effect on chronic disease management that was promised.

4.2.3 Impact on patient engagement, adherence, and quality of life

The third theme is about how AI affects quality of life, patient engagement, and sticking with treatment, all of which are important outcomes in managing chronic conditions. The descriptive results for

the "Clinical and patient outcomes and workflow" dimension show that respondents had a mostly positive view of the topic. The average scores for questions about patient engagement, adherence, and quality of life were between 3.60 and 3.85. This shows that healthcare professionals think AI tools can help patients be more involved in their care, better adhere to their treatment plans, and feel better overall. The item titled "AI contributes to improving quality of life" had the highest mean score (3.85). Other items that talked about AI-powered communication platforms and tools for better adherence also did very well.

The results of the inferential tests back up these ideas. We found a strong positive correlation ($r = 0.672$, $p < 0.001$) between the use of AI and clinical and patient outcomes. This, along with the significant regression coefficients for both use of AI and implementation/governance, suggests that interventions that use AI are linked to better outcomes at the patient level. Respondents say that workflow efficiency, communication, and disease self-management all get better when AI tools are used correctly and are built into well-governed systems. All of these things can indirectly improve engagement and adherence. The research we looked at in Chapter Two talks about different AI-based strategies that support these ideas. These include telemedicine platforms, mobile health apps, wearable tech, and smart monitoring systems. These technologies can give feedback, reminders, and alerts in real time, let doctors keep an eye on symptoms and treatment responses from afar, and make it easier for patients and healthcare teams to talk to each other all the time. AI can help patients better understand their conditions, follow their treatment plans, and live healthier lives by using these skills. This is especially important for people with chronic diseases who need to manage their own care for a long time.

The descriptive results do, however, include an important caveat: the item that asked if "patients generally trust AI-based recommendations" got a lower mean score (3.55), but it was still in the positive range. So, even though doctors can see clear benefits in terms of patient trust, adherence, and quality of life, they also think that patients might not fully trust AI yet. There is research that backs up this observation. Patients are worried about the "black box" nature of some AI systems, the possibility that care will become less personalized, and who is responsible when AI makes suggestions. So, the results of this study both show that AI has the potential to improve outcomes that are focused on the patient and show that problems with being clear, being able to explain things, and educating patients need to be fixed. Some ideas that might help build trust and get more people to use AI-enabled care are letting patients help design AI tools, making sure that it's clear how AI systems come to their conclusions, and making sure that clinicians are still involved in making decisions.

4.2.4 Summary of Integrated Findings

The study's main idea is supported by the discussion of both real-world results and existing research. This idea says that AI's effect on managing chronic diseases is determined by how the technology is used and the conditions at the system level. AI is seen as a useful way to improve the diagnosis and treatment of chronic diseases, especially when it is backed up by cross-disciplinary collaboration and high-quality data. Technological, infrastructural, and governance factors, such as interoperability, infrastructure adequacy, and supportive policies, are key enablers that determine how well AI can improve clinical and patient outcomes. AI-based tools improve patient engagement, treatment adherence, and quality of life, but patient trust in AI still needs more work. All together, the results show that strong implementation, integration, and governance structures along with smart use of AI lead to better clinical and patient outcomes and more efficient workflows. This conclusion fits with newer ideas in the literature that stress the importance of balancing sociotechnical factors in the digital transformation of health. The next chapter builds on these results to present the study's main conclusions, useful suggestions for those involved, and ideas for more research into how AI can help manage chronic diseases.

5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The main results of the study called "The Impact of Artificial Intelligence in Improving the Diagnosis and Treatment of Chronic Diseases" are shown in this chapter. Our study's main goal was to find out how using artificial intelligence (AI) and how it is implemented, integrated, and governed can improve the diagnosis and treatment of chronic diseases, as well as the flow of work in the clinic and the outcomes for patients. The research used a descriptive and correlational research design and used quantitative data from 205 healthcare workers who were asked to fill out a survey. A structured questionnaire with three main parts was used to collect data: (1) how AI can be used to improve diagnosis and treatment; (2) how AI is implemented, integrated, and governed; and (3) clinical and patient outcomes and workflow. We used SPSS to look at the data and used descriptive statistics, correlation analysis, multiple regression analysis, and reliability and validity tests.

In line with the main goal of the study, this chapter gives an overview of the main findings arranged according to the study's objectives and research questions. It then goes on to talk about the main conclusions that can be drawn from these findings. Then it gives a list of useful suggestions for healthcare organizations, policymakers, technology developers, and educational groups. The chapter also talks about the study's flaws that should be taken into account when figuring out what the results mean. It also suggests more research that will help us learn more about how AI can be used to manage chronic diseases.

5.2 Summary of Key Findings

This part gives a brief outline of the study's main results in relation to its three main goals and the research questions that went with them. The findings of the study demonstrate a generally positive perception among healthcare professionals regarding the effectiveness and value of artificial intelligence (AI) in chronic disease management. Regarding the first objective, participants reported a high overall mean score for the use of AI to improve diagnosis and treatment, indicating that AI is perceived to enhance diagnostic accuracy, clinical decision-making, treatment management, and workflow efficiency. A strong, positive, and statistically significant relationship was identified between AI utilization and clinical and patient outcomes, while regression analysis showed that AI use was a strong predictor of these outcomes. These findings suggest that the appropriate integration of AI into diagnostic and therapeutic processes is associated with improved care quality and effectiveness for patients with chronic diseases. The second objective focused on technological, infrastructural, and regulatory factors influencing AI implementation. Participants recognized government policies and financial support as important enablers of AI innovation and adoption in healthcare. However, inadequate technological infrastructure and difficulties related to data integration, interoperability, and exchange were identified as major barriers. The results further demonstrated a significant positive relationship between implementation, integration, and governance and clinical and patient outcomes and workflow. Regression analysis confirmed that this dimension was a strong and significant predictor of outcomes, highlighting the importance of effective system integration, implementation strategies, governance, and regulatory frameworks. Overall, the findings emphasize that policy support and investment can facilitate AI adoption, whereas infrastructure and interoperability challenges may limit its effective implementation.

The third objective examined the effects of AI on patient engagement, treatment adherence, and quality of life. Participants generally agreed that AI contributes positively to these patient-centered outcomes. Mean scores for indicators related to engagement, adherence, and quality of life ranged from 3.60 to 3.85, suggesting that AI-enabled communication platforms can increase patient involvement, support adherence to treatment plans, and improve quality of life. Correlation and regression analyses further supported significant relationships

between AI use, implementation and governance, and clinical and patient outcomes. Despite these positive findings, patient trust in AI-based recommendations received a comparatively lower, although still positive, mean score. This indicates that trust remains an important area requiring further attention. Greater transparency, explainability, and patient education may be necessary to strengthen confidence in AI technologies. Overall, the study indicates that AI has considerable potential to improve chronic disease diagnosis, treatment, patient engagement, adherence, workflow efficiency, and quality of life, while successful implementation depends on appropriate infrastructure, interoperability, governance, policy support, and sustained patient trust.

5.3 Conclusions (Answering the Research Questions)

The study findings, supported by the literature reviewed in Chapter Two, provide important conclusions regarding the factors influencing the use of artificial intelligence (AI) to improve the diagnosis and treatment of chronic diseases. Overall, effective AI utilization, supportive infrastructure, strong governance, and human acceptance were identified as important factors influencing clinical and patient outcomes. Regarding the primary research question, effective use of AI tools was found to be a central driver of improved clinical and patient outcomes. The high mean score for AI use and its strong positive correlation with clinical and patient outcomes ($r = 0.67$, $p < 0.001$), together with a significant regression coefficient ($\beta = 0.43$, $p < 0.001$), indicate that greater AI utilization is associated with improved diagnostic and therapeutic outcomes and more efficient workflows. The findings also demonstrated that implementation, integration, and governance are essential conditions for achieving AI benefits. This dimension showed a strong positive relationship with outcomes ($r = 0.66$, $p < 0.001$) and a significant regression coefficient ($\beta = 0.41$, $p < 0.001$). These results emphasize the importance of adequate computing resources, connectivity, interoperable electronic health records, and effective integration with existing health information systems.

Data governance, regulatory frameworks, privacy protection, cybersecurity, and supportive government policies were also identified as important determinants of AI effectiveness and acceptability. Participants viewed government policies and funding as important enablers of AI innovation, while data integration and interoperability problems remained significant barriers. In addition, staff acceptance, professional trust, perceived usefulness, and willingness to use AI-supported tools were identified as important socio-human factors that can influence successful implementation. For Sub-question 1, the findings indicate that policy and funding are major enablers of AI adoption, whereas inadequate technological infrastructure, limited interoperability, and evolving regulatory frameworks remain significant barriers. Insufficient hardware, software, connectivity, and system integration may restrict large-scale implementation. Furthermore, challenges related to liability, validation, privacy, cybersecurity, and data governance highlight the need for clear regulatory and ethical frameworks to ensure safe and effective AI use.

For Sub-question 2, the findings indicate that AI can positively influence patient engagement, treatment adherence, and quality of life. AI-enabled communication platforms, personalized feedback, monitoring systems, reminders, wearable technologies, and decision-support tools can increase patient involvement and support chronic disease self-management. The positive findings regarding treatment adherence suggest that AI can help patients follow treatment plans more consistently. Quality of life received the highest mean score within the outcomes dimension, indicating perceived benefits in symptom management, prevention of complications, and overall patient well-being. However, patient trust in AI-based recommendations received a comparatively lower, although still positive, mean score. This suggests that trust remains an emerging issue requiring greater attention. Transparency, explainability, comprehensible communication, and patient-centered approaches are therefore important for strengthening confidence in AI. Overall, the

study concludes that AI has significant potential to improve chronic disease management, but its successful and sustainable implementation depends on effective technology, infrastructure, governance, regulation, professional acceptance, and patient trust.

5.4 Recommendations

Based on what the study found and what it concluded, the following suggestions are made for how key stakeholder groups can get the most out of AI in managing chronic diseases. The study recommends coordinated actions among healthcare institutions, policymakers, technology developers, and educational institutions to support the safe and effective adoption of AI in chronic disease management. Healthcare organizations should invest in secure, scalable IT infrastructure, interoperable EHR systems, and standardized data formats to facilitate data exchange and AI integration. Multidisciplinary teams involving clinicians, data scientists, IT specialists, and health informatics professionals should collaborate with frontline staff to ensure that AI solutions are clinically relevant and compatible with existing workflows. Continuous staff training and professional development should strengthen AI knowledge, confidence, and appropriate use.

Policymakers and regulators should establish comprehensive regulations governing healthcare data sharing, privacy, security, and AI use. They should also develop standardized processes for clinical validation, certification, and continuous monitoring of AI algorithms. Governments and funding agencies should support research and implementation, particularly in underserved and resource-limited settings, while providing incentives for safe AI adoption and infrastructure development. Technology developers should design user-friendly systems with clear visualizations, explainable AI methods, and workflows aligned with clinical practice. Multilingual and culturally appropriate interfaces should address local languages, cultural norms, and health literacy, while collaboration with local stakeholders should ensure that systems meet specific community and healthcare needs. Educational institutions should integrate AI, data science, and digital health into medical, nursing, pharmacy, and health informatics curricula. Training should emphasize interpretation of AI outputs, data quality, multidisciplinary collaboration, and practical applications. Students should also be encouraged to undertake chronic disease-related AI research and critically examine its ethical, legal, and social implications to promote responsible future use.

5.5 Study Limitations

Even though this study's results are useful for understanding how AI might affect the diagnosis and treatment of long-term illnesses, there are some issues that need to be pointed out: The study has several limitations. First, the purposive sample of 205 participants from selected healthcare settings may not fully represent different regions, institutions, or clinical specialties, limiting the generalizability of the findings. Second, the descriptive-correlational, cross-sectional design identifies relationships between variables but cannot establish causal effects; therefore, observed associations between AI use and improved outcomes cannot confirm causation. Third, self-reported questionnaire data may be influenced by response and social desirability biases, potentially leading participants to overestimate AI benefits or underestimate challenges. Finally, the study focused mainly on AI use, implementation, integration, governance, and outcomes, without directly assessing factors such as cost-effectiveness, patient safety, ethical issues, or long-term economic impacts. It is important to be aware of these limitations when trying to understand the study's results and plan future research that will help us get a better, more complete picture of how AI can help diagnose and treat chronic diseases.

5.6 Suggestions for Future Research

After looking at the study's results and its limitations, the authors suggest the following areas for future research that will help us learn more about the role of AI in managing chronic diseases:

Future research should adopt longitudinal, experimental, or quasi-experimental designs to move beyond correlational findings and examine the long-term effects of AI interventions on clinical and patient outcomes. Comparative studies could assess AI-assisted care against standard care or evaluate outcomes before and after AI implementation. Larger and more diverse samples should also be recruited across different geographic regions, healthcare institutions, and clinical specialties to improve generalizability and examine the influence of organizational and health-system factors.

Further research should investigate AI applications within specific chronic diseases, including diabetes, COPD, cardiovascular, and liver diseases, to identify disease-specific benefits in diagnosis, risk assessment, treatment planning, and self-management. Patient perspectives should also be examined through qualitative approaches such as interviews, focus groups, and patient narratives, particularly regarding trust, understanding, and concerns about AI-enabled care. In addition, economic evaluations are needed to assess the cost-effectiveness and long-term financial impact of AI, including implementation costs, hospitalization, complications, and potential healthcare savings. Finally, future studies should explore ethical, legal, and organizational issues such as accountability, algorithmic bias, changing professional roles, and organizational change. Such research could support comprehensive frameworks for responsible, sustainable, and patient-centered AI implementation in chronic disease management.

5.7 Closing Statement

Finally, this study shows how artificial intelligence is becoming more and more important as a revolutionary tool for managing long-term illnesses. The study shows that using AI effectively, along with strong infrastructure, strong implementation and governance frameworks, and involved healthcare professionals, is strongly linked to better clinical and patient outcomes. This is solid evidence that AI can make a real difference in both patient well-being and health system performance. As the number of people with chronic illnesses continues to rise, healthcare systems need to find ways to make care more efficient, fair, and patient-centered. The smart and responsible use of AI could help with this.

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