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Role of Artificial Intelligence in Advancing Value-Based Healthcare – Opportunities and Challenges: A Scoping Review

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Abstract

Background: *Healthcare systems worldwide face an escalating burden of increasing healthcare costs and inconsistent clinical outcomes. Value-based healthcare (VBHC) emerged to bring a fundamental shift in the healthcare sector, focusing on improved patient outcomes and cost-effectiveness to maximise the overall quality of care. The advent of artificial intelligence (AI), including machine learning (ML), deep learning and natural language processing (NLP), offers opportunities to advance VBHC by improving diagnostic accuracy, reducing wasteful expenditure, and personalising care delivery.*
Objectives: *This scoping review aims to: (i) identify the opportunities associated with AI technology adoption for advancing VBHC, (ii) ascertain the challenges and barriers to AI adoption in VBHC initiatives, and (iii) suggest future directions for overcoming these challenges.*
Methods: *A scoping review was conducted as per the Joanna Briggs Institute framework and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines. Articles published between 2020 and 2025 were selected for the study from PubMed, Directory of Open Access Journals, Scopus and Web of Science.*
Results: *The results emphasized the role of AI to advance the VBHC across the three attributes. In the monetary value domain, ML-based predictive modelling, hybrid deep learning models and AI-powered administrative automations showcased noticeable cost savings and resource optimization. In the patient-centred care domain, AI-enabled personalised medicine, integration of patient-reported outcome measures (PROMs) and patient-reported experience measures (PREMs), and enhanced patient engagement through virtual health technologies. In the quality of care domain, clinical decision support systems, disease prediction algorithms and AI-powered diagnostic tools improve the accuracy of diagnostics and patient outcomes. However, adoption is obstructed by data fragmentation, workforce resistance, immature governance frameworks, and algorithmic opacity.*
Conclusions: *Artificial intelligence contains noticeable potential to advance VBHC delivery and implementation. However, to realise this potential, there is an increased need to stress the importance of explainable AI frameworks, investment in AI literacy, effective data governance and national-level regulatory frameworks. Future research should focus on empirical studies, integration of patient-generated data into the ML model development AI equity validation.*

Keywords: *Value-based healthcare, VBHC, PROMS, PREMS, machine learning, deep learning, Natural Language Processing (NLP)*

Highlights of the Study:

1. This scoping review papers assess the impact of Artificial Intelligence technologies on the Value-Based Healthcare Delivery.
2. The study shortlisted and analyzed 33 articles from 2020 to 2025 years using the PRISMA-ScR framework.
3. Evidence suggested the improvement in diagnosis accuracy and cost effectiveness using AI, which are core tenets of Value-Based Healthcare.
4. Adoption of AI is limited due to ethical concerns, data privacy issues and lack of transparency in Algorithms.

5. Future success relies on strong governance, legal frameworks and explainable AI models.

1. Introduction

Global healthcare spending has reached US$ 8.3 trillion, approximately 10% of global GDP, and a significant gap remains between the care that patients receive and the ideal standard of care [1]. In the US, wasteful healthcare spending amounts to the GDP of the world's 17th-largest economy. The main reason for this excessive spending can be attributed to over-treatment, failures in care delivery, fraud, the provision of low-quality care, administrative complexities, poor care coordination and resource planning gaps [2]. In the European Union, healthcare expenditure per capita is forecasted to increase to an average rate of 2.7%, reaching 10.2% of GDP by 2030 from 8.8% in 2018 [3]. This presses the immediate need for a shift from volume of services to value-based care (VBC) that focuses on clinical outcomes without increased healthcare costs [1].

In recent times, the rapid expansion of artificial intelligence (AI) has fundamentally transformed different facets of healthcare, providing impactful solutions to various critical medical challenges. With the increased availability of healthcare data and advanced analytical methods, AI typically mimics human cognitive abilities [4]. Its historical roots can be traced to the 1950s as a continuous field of study dedicated to enabling devices, such as computers, to simulate human mental abilities, such as cognition, learning, decision-making, judgement and language usage [5]. Globally, healthcare systems are embracing AI as they strive to achieve the 'quadruple objective' to enhance patient health and well-being, improve healthcare access, improve working conditions for healthcare workers and provide cost effectiveness. This objective is directly aligned with value-based healthcare (VBHC), which delivers high-quality clinical outcomes relative to the cost of care [6]. From the review of literature as per the inclusion criteria there are no studies that focus on all three attributes of VBHC, which justified the selection of the review.

Artificial intelligence technologies have the potential to address significant economic challenges inherent to healthcare systems. With the help of large datasets, AI can identify patterns surpassing human performance and excellence, leading to precise diagnosis. Machine learning (ML) can assist physicians in optimising treatment regimens and streamlining processes, such as laboratory testing, which can benefit organisations with low-cost treatments and processes. Artificial intelligence can bring automation to high-demand areas in the emergency department, where AI can reduce waiting times and improve patient flow. Additionally, AI can reduce human errors and provide more accurate results in less time [7]. The evolution of AI has been greatly accelerated by rapid advancements in computing infrastructure, which have improved processing speed, storage capacity and cloud computing capabilities [8]. Additionally, the emergence of large language models (LLMs), such as GPT-4, promoted the adoption of artificial general intelligence. These LLMs have the potential to improve patient care and medical access and optimise clinical practice. Without proper regulation and oversight, the widespread use of LLMs could introduce unintended risks and consequences for patient health [9]. Artificial intelligence can be a transformative solution in improving clinical outcomes at lower costs, which aligns with the foundation principles of VBHC.

Nonetheless, the application of AI in VBHC faces multiple challenges. Most AI research is restricted to proof of concept and exploratory stages [8]. The existing gap in the actual implementation of AI ethics frameworks and guidelines is widely noticeable and can lead to a 'translation gap'[10]. Artificial intelligence interpretability and explainability were also not transparent, leading to a 'black box' phenomenon that hinders trust, accountability and clinical acceptance. Automation bias can cause healthcare workers to accept the guidance of AI without critical judgement, causing serious risks to patients. Legal frameworks and policies must keep pace with the evolution of AI technologies, which is challenging due to the rapid advancement in the AI field. For reliable AI, there is a requirement for large, high-quality datasets,

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and with limited data, there is a risk of overfitting that can lead to unreliable predictions and the lack of generalisability. Moreover, cyberattacks and data breaches can make AI more vulnerable to health data breaches[11].

This paper aims to perform a scoping review to understand the impact of various AI technologies on advancing VBHC by exploring and synthesising the existing knowledge base through a scoping literature review.

2. Research Questions

The key questions to be addressed by the end of the scoping review are as follows:

- What are the opportunities associated with the adoption and implementation of AI technologies for advancing VBHC?
- What challenges to adoption are reported in the literature regarding the use of AI in VBHC initiatives?
- What recommendations have been suggested in the literature to overcome these challenges and barriers, thereby supporting the advancement of VBHC using AI?

2.1 Research Objectives

- To understand the opportunities associated with the adoption and implementation of AI technologies for advancing VBHC
- To ascertain the challenges related to the adoption of AI in VBHC initiatives
- To suggest the list of future directions regaring the usage of AI in VBHC initiatives

3. Methods

3.1 Study Design and Strategy

A scoping review was conducted according to the Joanna Briggs Institute and the framework of Arksey and O'Malley [12]. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) was used to conduct the review [13]. Since this study aims to perform a literature review on a broader scale to understand the impact of AI technologies on the VBHC concept, a scoping review is ideal for answering the research questions.

A literature search was performed based on patient or problem of interest (P), intervention (I), comparison (C) and outcomes (O) [14]. For the current review, the intervention component AI was not used for comparison with other technologies. Hence, comparison (C) was not considered, and the PIO framework was adopted as presented in the (Table 1).

Table 1 PIO Framework

Component	Description
Population (P)	Healthcare systems
Intervention (I)	Artificial intelligence technologies
Outcomes (O)	Opportunities and advantages for advancing value-based healthcare Challenges and barriers to utilising AI in value-based healthcare

3.2 Study Eligibility

Multiple electronic databases – PubMed, Scopus, Directory of Open Access Journals and Web of Science – were searched for relevant manuscripts. Medical subject heading 2025 was used to select VBHC and AI terms in the literature review.

The terms that were used in the search are as follows in the (Table 2):

Table 2 Key Terms on VBHC and AI

Value-based healthcare	Artificial intelligence
VBHC, value based healthcare, value based health care, value based healthcare, value-based healthcare	AI (artificial intelligence), computational intelligence, computer reasoning, computer vision systems, knowledge acquisition (computer), knowledge representation (computer), machine intelligence, machine learning, natural language processing, deep learning, convolutional neural networks, recurrent neural networks, generative adversarial networks, robotics

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Owing to a shortage of articles directly involving the above terms, especially VBHC, the following search terms were used to identify additional literature as provided in the (Table 3).

Table 3 Key specific terms on VBHC and AI

Value-based healthcare	Artificial intelligence
Pay for performance, accountable care organisation, alternative payment model, value-based care, diagnostic accuracy, personalized medicine, treatment planning, medical error reduction, cost-effectiveness, operational efficiency, resource allocation, patient engagement, physician burnout	Predictive analytics, black box, algorithm bias

Additionally, the inclusion and exclusion criteria that were followed are as follows:

Inclusion Criteria

- Articles published within the past five years (i.e. 2020 to 2025).
- Articles published in the English language.
- Articles published in the open-access scientific journals.
- Articles addressing the concepts of VBHC using AI and its associated technologies.
- There was no global restriction in the selection of articles.

Exclusion Criteria

- Articles published before 2020 and after 2025
- Articles that are not published in English
- Articles that are published in non-scientific journals
- Articles addressing AI in healthcare without a direct connection or relevance to value-based healthcare attributes

4. Results

4.1 Screening Results

The initial database search yielded 1027 papers. After removing duplicates, a total of 615 manuscripts remained that focused on AI in healthcare in relation to opportunities and challenges. Of these, 615 records went through title and abstract screening, which excluded 431 papers based on their relevance to the research question, resulting in 184 manuscripts. Following full-text screening, excluding editorial papers and main texts not addressing VBHC and AI, 33 papers were included. There were 9 empirical (27%) and 24 non-empirical studies (73%) in the final papers. Search and selection results are represented in the (Figure 1) below.

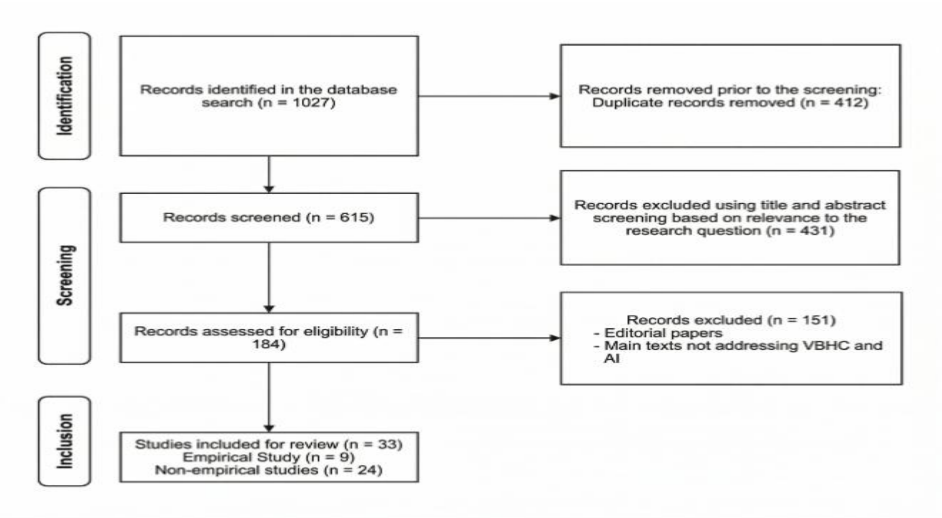


Figure 1 PRISMA flow chart of search results and selection of results

The screening of the articles revealed increased research in the field of healthcare in the last five years. Methodologically, the review identified the application of supervised ML techniques in healthcare. Predictive modelling for disease detection and regression in the area of predicting healthcare costs were the most applied use cases identified in the review. Additionally, the use of natural language processing (NLP) in clinical documentation automation and data extraction was observed in the studies. Geographical research was more concentrated in the regions of North America and Europe, highlighting the differences in implementing AI into VBHC. Table 3 below provides the representation of study type, country or region it belongs to, specific AI technology studied, and VBHC attribute mentioned.

Table 3 Shortlisted articles and their study types, geographical context, AI technologies studies and VBHC attributes presented

Ref.	Author(s) & Year	Type of Study	Country/Region	AI Technology	VBHC Attribute
[1]	Kehyayan et al. 2025	Concept Analysis	Qatar/Canada	Not applicable (framework paper)	All three (definitional)
[2]	Crowson & Chan 2020	Commentary	USA/Canada	ML, Predictive Analytics, CDS, NLP	Monetary and Quality
[3]	Kacew et al. 2021	Modelling Study	USA	Diagnostic AI algorithms	Monetary and Quality
[4]	Poalelungi et al. 2023	Review	Romania	ML, Deep Learning, NLP, Digital Pathology	Quality and PCC
[5]	Bjerring & Busch 2021	Commentary	Denmark	Black-box AI, Deep Learning	PCC
[6]	Dranove & Garthwaite 2022	Working Paper	USA	Diagnostic AI, CDS	Monetary
[7]	Botha et al. 2024	Scoping Review	Ghana/Global	Computer Vision, ML, Knowledge Representation	Quality and PCC
[8]	Hennrich et al. 2024	Qualitative	Germany	Diagnostics, Biomedical Research, Admin AI	All three attributes
[9]	Hendrix et al. 2022	Methodological Review	USA	Clinical AI (diagnostics, decision support)	Monetary and Quality
[10]	Kim et al. 2020	Retrospective Study	South Korea/USA/UK	Deep Learning AI	Quality
[11]	Raclin et al. 2022	Protocol	USA (Stanford)	ML algorithms, eHealth	Quality and PCC
[12]	Bian et al. 2023	Survey Study	China	Internet Health Care Technology	PCC and Quality
[13]	Khanna et al. 2022	Review	India/USA/EU	Diagnostic AI, Precision Medicine, Imaging AI	Monetary and Quality
[14]	Kalusivalingam et al. 2026	Mixed Methods	Not specified	NLP, Reinforcement Learning, VHAs	PCC and Quality
[15]	Tariq et al. 2023	Case Studies	USA	Surgical Robotics, Predictive Analytics	All three attributes
[16]	Verma et al. 2022	Research Article	Norway	ML Regression, Classification	Quality and PCC
[17]	Weerarathna 2024	Book Chapter	India	Medical Imaging AI, EHR AI, Surgical Robots	Quality and PCC
[18]	Poveda et al. 2022	Commentary	Spain	NLP, EHR Analytics	Monetary
[19]	Pamulaparthyvenkata 2023	Retrospective Study	USA	EHR, Genomic Databases, Bioinformatics	All three attributes
[20]	Davis et al. 2025	Scoping Review	USA/Canada	NLP, ML, Integrated Care AI	PCC and Quality
[21]	Pamulaparthyvenkata & Avacharmal 2021	Conceptual	USA	ML, Predictive Analytics, Risk Scoring	Monetary and Quality
[22]	Nagarajaiah et al. 2025	Conference Paper	India	XAI, Federated Learning, Edge Computing	Quality and PCC
[23]	Shah et al. 2025	Review	USA	ML, NLP, LLMs,	All three attributes

				Generative AI	
[24]	Bhatti et al. 2023	Research Article	Pakistan/Saudi Arabia	Deep Learning (VGG, SAE, DNN hybrids), SHAP	Monetary
[25]	Ahluwalia 2025	Systematic Analysis	India	NLP, Predictive Analytics, Digital Front Door AI	PCC and Quality
[26]	Kumar et al. 2023	Mixed Methods	India/UK	Responsible AI, Precision Medicine AI	Monetary and PCC
[27]	Alowais et al. 2023	Review	Saudi Arabia	ML, NLP, Computer Vision, CDS, VHAs	Quality and PCC
[28]	Salunkhe et al. 2022	Case Study	India	Predictive Analytics, Wearables	PCC and Quality
[29]	Chaturvedi et al. 2025	Review	India/Global	AI Diagnostics, Wearables, IoMT, 5G	PCC and Quality
[30]	Karaferis et al. 2024	Review	Greece/EU	Decision Support, IoMT, RPM, Robotics	PCC and Quality
[31]	Shiwlani et al. 2024	Systematic Review	USA/Pakistan	ML, AI Diagnostics, Predictive Analytics	Monetary and Quality
[32]	Folkvord et al. 2024	Innovation Report	EU Multinational	PROMs/PREMs Digital Tools, PGHD Platforms	All three attributes
[33]	Macri & Roberts 2023	Opinion	Canada	Clinical AI, ML	PCC

The 33 included articles for the review comprise 9 empirical studies and 24 non-empirical studies. These studies are a mix of narrative scoping reviews, conceptual analysis, commentaries, protocols, and book chapters. From the geographical perspective, most of the studies are concentrated in North America (n = 14) and Europe (n = 9), with minor representation from Asia (n=7) and the Middle East (n=2). Figure 2 presents the geographical origin of studies globally.

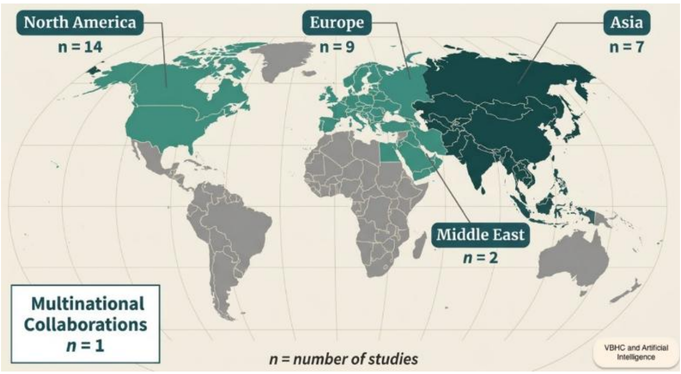


Figure 2 Geographical Map describing the origin of studies

Observations in the publication years revealed that there is a marked increase in the output of publications from 2022 onwards. This is mostly correlating with the post-pandemic research acceleration in digital health and value-based healthcare. Figure 3 presents the percentage share of studies region wise.

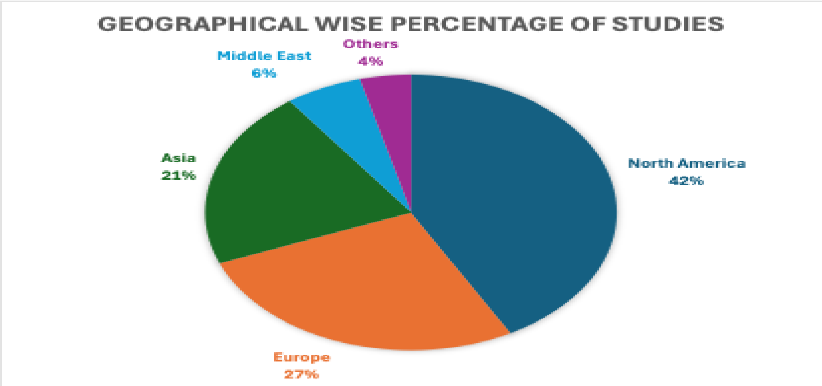
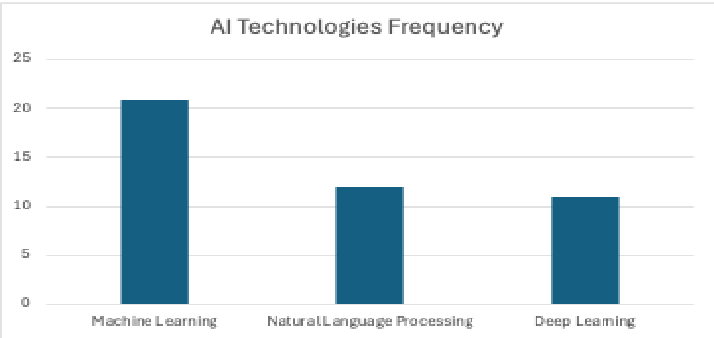


Figure 3 Percentage share of studies from geographies

Machine Learning is the most studied and reviewed technology in the AI domain. Natural Language Processing and Deep Learning are equally interested in reviewing and exploring the space of VBHC. Figure 4 presents the AI Technologies frequency from the list of studies



. Figure 4 AI Technologies frequency from studies

4.2 Thematic Distribution of the included studies across VBHC Domains (n=33)

The VBHC concept relies on three attributes: monetary value of health services, quality of care and patient-centred care (PCC) [29]. Figure 5 presents each criterion in detail. Each study was narrowed down to check the criteria for accuracy.

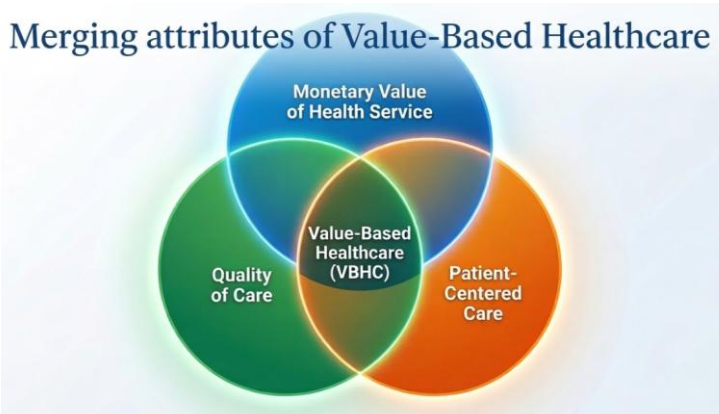


Figure 5 Three attributes of Value-Based Healthcare

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Analysis of thirty-three articles primarily identified three clusters of findings, each related to one attribute of VBHC [29]. Additionally, as a fourth item, challenges and barriers to AI adoption were analysed. These themes are not mutually exclusive. 18 out of 33 articles addressed 2 or more domains simultaneously.

Quality of care was the most extensively studied and addressed among the 3 attributes of VBHC, of which 16 out of 33 included articles identified the AI's contribution. Clinical decision support systems and outcome prediction using the PROMs and machine learning, and prediction of disease, and population health were some of the use cases in which the AI is playing a major role.

Patient Centred Care domain presented in 15 out of 33 included articles were focused on improving the patient care by involving and integrating prompts and using the patient-generated health data like PREMS and PROMS to engage patients in the care, and the focus is more on the Personalized Medicine and Precision Care. 4 of these articles reported from Empirical Findings.

11 articles address the contribution of AI to the monetary value of healthcare services, of which three are from empirical evidence, and eight were analysed and extracted from non-empirical or conceptual analyses. These studies highlighted the potential of AI technologies in predicting healthcare costs and modelling, automating the administrative tasks and resource optimization. Table 4 presents the thematic attributes of VBHC in empirical and non-empirical studies.

Table 4 Thematic attributes of VBHC and counts

Thematic attributes of VBHC	**Total (n)**	**Empirical (n)**	**Non- Empirical (n)**	**Unique Findings**
Monetary Value of Health Services	11	3	8	6
Quality of Care	16	5	11	7
Patient-Centred Care	15	4	11	8
Challenges & Barriers to Adoption	18	4	14	—

4.3 Attribute-specific use cases, opportunities and AI Technologies

Below are the VBHC attributes- wise identified use cases and corresponding opportunities from the shortlisted articles.

Table 5 Attribute 1: Monetary Value of Health Services

4.3.1 Attribute 1: Monetary Value of Health Services (n = 11 articles; 13 opportunities) See Table 5

#	Use case	Opportunities	AI Technology	Key Sources
Predictive Cost Modelling				
1	Hybrid Deep Learning Cost Prediction Models (CNN and RNN; R^2 up to 0.99)	Predictive Cost Modelling	CNN and RNN hybrid architecture	Bhatti et al. [18]
2	ML-Driven Proactive Financial Risk Stratification (high-cost cohort identification)	Predictive Cost Modelling	Supervised ML	Pamulaparthyvenkata & Avacharmal [23]
3	Risk-Adjusted Pricing, Prospective Budgeting & Value-Based Contract Models	Predictive Cost Modelling	Machine Learning / Predictive Analytics	Crowson & Chan [2]
Diagnostic Efficiency & Cost Avoidance				
4	AI-Assisted Colorectal Cancer Genotyping (USD 400M projected national savings)	Diagnostic Efficiency & Cost Avoidance	Deep Learning / Diagnostic AI	Kacew et al. [17]
5	Deep CNNs for Surgical Pathology Analysis (40 min to 3 min, no accuracy loss)	Diagnostic Efficiency & Cost Avoidance	Convolutional Neural Networks	Weerarathna [4]
6	AI Hip Fracture Imaging (false-negative rate reduced from 17% to 9%)	Diagnostic Efficiency & Cost Avoidance	Computer Vision / Deep Learning	Weerarathna [4]

7	Diagnostic AI vs Treatment AI: Cost-Effectiveness Ratio Analysis	Diagnostic Efficiency & Cost Avoidance	ML (comparative analysis)	Khanna et al. [28]
Administrative Automation & Resource Optimisation				
8	AI Prior Authorisation Automation (22% work queue reduction; 300 staff hrs/month saved)	Administrative Automation	ML / Rule-based AI	Shah et al. [33]
9	Claims Processing & Billing Automation	Administrative Automation	NLP / Robotic Process Automation	Shah et al. [33]; Dranove & Garthwaite [40]
10	NLP Applied to EHRs for Treatment Cost Quantification at Scale	Administrative Automation	Natural Language Processing	Poveda et al. [24]
11	AI-Enabled Pharmaceutical Value-Based Contracting (outcome-based payer negotiations)	Administrative Automation	NLP on real-world evidence	Poveda et al. [24]
12	Predictive Analytics for Bed Management & OR Scheduling (21% OR overtime reduction)	Resource Optimisation	Predictive Analytics / ML	Shah et al. [33]
13	AI-Driven Healthcare Waste Reduction (over-treatment, care coordination failure)	Resource Optimisation	Machine Learning	Crowson & Chan [2]; Hennrich et al. [19]

Table 6 Attribute 2: Quality of Care

4.3.2 Attribute 2: Quality of Care (n = 16 articles; 16 opportunities) See Table 6

#	Use case	Opportunities	AI Technology	Key Sources
Diagnostic Accuracy & Imaging				
1	AI Mammography Screening Algorithm (AUROC 0.959 vs 0.810 unaided radiologist; reduced false-positive recall)	Diagnostic Accuracy & Imaging	Deep Learning / Computer Vision	Kim et al. [32]
2	Deep CNNs for Surgical Pathology (sample analysis: 40 min to 3 min, no accuracy loss)	Diagnostic Accuracy & Imaging	Convolutional Neural Networks	Weerarathna [4]
3	AI Hip Fracture Imaging (false-negative rate: 17% to 9%)	Diagnostic Accuracy & Imaging	Computer Vision / Deep Learning	Weerarathna [4]
Clinical Decision Support Systems (CDSS)				
4	IBM Watson for Oncology	CDSS	Knowledge Representation / ML	Alowais et al. [7]; Botha et al. [30]
5	PathAI Diagnostic Pathology Assistant	CDSS	Deep Learning	Alowais et al. [7]; Botha et al. [30]
6	Aidoc Radiology AI	CDSS	Computer Vision / Deep Learning	Alowais et al. [7]; Botha et al. [30]
7	AI Chatbots for Chronic & Primary Care (dietary guidance, CBT, smoking cessation)	CDSS	NLP / Conversational AI	Alowais et al. [27]
8	AI for Orthopedic Surgery — Value-Based Care Alignment (surgical robotics, predictive analytics)	CDSS	Surgical Robotics / Predictive Analytics	Tariq et al. [34]
Outcome Prediction Using PROMs & ML				
9	PROMs and Supervised ML for Musculoskeletal Outcome Prediction (pain, work capacity)	Outcome Prediction	Random Forest, Gradient Boosting, SVM, Neural Networks	Verma et al. [15]; Raclin et al. [25]
10	ML-Assisted Outcome Stratification Embedded in VBHC Contracts	Outcome Prediction	Supervised ML	Verma et al. [15]; Raclin et al. [25]
Disease Prediction & Population Health				
11	Computer Vision and Knowledge Representation Systems (29 empirically validated AI tools mapped)	Disease Prediction & Population Health	Computer Vision / Knowledge Representation	Botha et al. [30]
12	Continuous ML Monitoring for	Disease Prediction &	ML / Real-time	Weerarathna [4];

	Early Patient Deterioration Detection	Population Health	analytics	Botha et al. [30]
13	AI Risk Stratification for Early Disease Detection (cancer, chronic disease, deterioration)	Disease Prediction & Population Health	Machine Learning	Weerarathna [4]; Nagarajaiah et al. [16]; Chaturvedi et al. [22]; Karaferis et al. [37]; Shiwlani et al. [26]
14	AI-Powered Wearable Devices (personalised exercise feedback, real-time adherence monitoring)	Disease Prediction & Population Health	IoT + ML	Alowais et al. [7]; Karaferis et al. [37]
15	AI-Powered Prostheses — Myoelectric Signal Detection & Movement Prediction	Disease Prediction & Population Health	Deep Learning / Signal Processing	Weerarathna [4]
Operational Quality				
16	Teleconsultation Platforms with AI Triage (improved patient satisfaction & medication adherence)	Operational Quality	NLP / Reinforcement Learning	Kalusivalingam et al. [35]

Table 7 Attribute 3: Patient-Centred Care

4.3.3 Attribute 3: Patient-Centred Care (n = 15 articles; 19 opportunities) See Table 7

#	Variable / Technology	Opportunities	AI Method / Tool	Key Source(s)
Personalised Medicine & Precision Care				
1	Personalised Medicine via Genomic Profiling, Biomarker & Environmental Factor Integration	Personalised Medicine & Precision Care	ML / Bioinformatics	Poalelungi et al. [8]; Weerarathna [4]; Pamulaparthyvenkata [23]; Nagarajaiah et al. [16]; Shah et al. [33]; Alowais et al. [7]; Chaturvedi et al. [29]
2	AI for Continuous Glucose Monitoring & Personalised Insulin Regulation (diabetes management)	Personalised Medicine & Precision Care	ML / Reinforcement Learning	Kalusivalingam et al. [14]; Chaturvedi et al. [22]
3	AI Integration of Lifestyle, Phenotypic & Experiential Data into Care Planning	Personalised Medicine & Precision Care	Machine Learning	Pamulaparthyvenkata [23]
4	AI-Powered Prostheses — Personalised Movement Prediction & Autonomy Enhancement	Personalised Medicine & Precision Care	Deep Learning / Signal Processing	Weerarathna [4]; Karaferis et al. [37]
Patient Engagement & Virtual Health Technologies				
5	Virtual Health Assistants integrating NLP and Reinforcement Learning (improved satisfaction & adherence)	Patient Engagement & Virtual Health	NLP and Reinforcement Learning	Kalusivalingam et al. [35]
6	AI-Powered Patient Portals (34% improvement in patient satisfaction)	Patient Engagement & Virtual Health	NLP / ML	Ahluwalia [38]
7	AI Appointment Scheduling Systems (28% reduction in scheduling inefficiency)	Patient Engagement & Virtual Health	Machine Learning	Ahluwalia [38]
8	Medication Reminder & Adherence Platforms (42% increase in preventive care engagement)	Patient Engagement & Virtual Health	NLP / Conversational AI	Ahluwalia [38]; Kalusivalingam et al. [35]
9	Remote Patient Monitoring via AI-Enabled Wearables & Sensors (reduced inpatient burden)	Patient Engagement & Virtual Health	IoT and ML	Karaferis et al. [37]; Chaturvedi et al. [29]
10	AI-Assisted Care Coordination for Social Determinants of Health (population scale)	Patient Engagement & Virtual Health	ML / Population Analytics	Davis et al. [27]
11	Internet Healthcare Technology Adoption — AI-Enabled Platforms	Patient Engagement & Virtual Health	AI-enabled digital platforms	Bian et al. [21]

	for Professionals & Patients			
PROMs, PREMs & Patient-Generated Health Data (PGHD)				
12	PROMs (Patient-Reported Outcome Measures) integrated with ML for outcome stratification	PROMs / PREMs / PGHD Integration	Machine Learning	Raclin et al. [11]; Verma et al. [16]; Folkvord et al. [32]
13	PREMs (Patient-Reported Experience Measures) integrated with AI clinical systems	PROMs / PREMs / PGHD Integration	Machine Learning	Raclin et al. [25]; Folkvord et al. [3]
14	PGHD (Patient-Generated Health Data) — EU IMPROVE Project multinational framework	PROMs / PREMs / PGHD Integration	ML / Data Integration	Folkvord et al. [3]
15	Digital PROMs/PREMs Embedded in Outcome-Based VBHC Contracts	PROMs / PREMs / PGHD Integration	Machine Learning	Raclin et al. [25]; Pamulaparthyvenkata [23]; Folkvord et al. [3]
Ethical Foundations of Patient-Centred AI				
16	Explainable AI (XAI) / Responsible AI Design — mediates AI adoption to patient value outcomes	Ethical Foundations	Explainable AI (XAI)	Kumar et al. [20]; Bjerring & Busch [41]
17	Shared Decision-Making AI Tools — transparent, interpretable architectures for informed consent	Ethical Foundations	XAI / Interpretable ML	Bjerring & Busch [41]
18	12-Value Ethical Framework for AI-Assisted Oncology Consultations (transparency, equity, autonomy)	Ethical Foundations	Conceptual / Values Framework	Macri & Roberts [39]
19	Patient Cognitive Engagement as Critical Mediating Variable in Responsible AI Pathway	Ethical Foundations	Structural Equation Modelling	Kumar et al. [20]

4.4 Empirical Studies

4.4.1 Clinical Outcome Prediction and Optimisation

The majority of studies explaining the development and validation of ML Models have been designed to improve the predictive accuracy related to patient outcomes, which is a core element of VBHC. Machine learning models can predict short-term outcomes related to pain and the ability to work using the patient-reported outcome measures datasets. The same study also highlighted the challenges related to the prediction of complex outcomes, such as referral advice [15]. In the field of precision medicine, AI frameworks have successfully demonstrated high accuracy (above 92%) in disease diagnosis and improved explainability with explainable AI (XAI) techniques, such as SHAP and LIME. In addition, significant concerns exist regarding the performance of low-resource devices, particularly the scalability and deployment issues in rural settings, which increase accessibility [16].

4.4.2 Economic and Resource Optimisation

The cost component of the value equation was analysed using ML applications. In diagnostics, a financial and clinical modelling study compared algorithms for colorectal cancer genotyping against standard care methods. The model generated quantitative projections that showed the potential to cut costs while maintaining diagnostic accuracy [17]. In relation to predictive cost management, quantitative empirical research has developed hybrid deep learning models, such as VGG-SAE, VGG-DNN and SAE-DNN, to predict healthcare provider costs. These models achieved high predictive performance, with an R-squared value of up to 0.99 on two real healthcare datasets, demonstrating efficient and accurate cost prediction [18]. Another qualitative study reached expert consensus on AI application, identifying resource optimisation and process acceleration as key value propositions among six derived from 15 core business objectives [19].

4.4.3 Patient and Professional Adoption and Engagement

Empirical studies have also focused on human factors that influence the effective integration of AI into VBC models. A mixed-methods study aimed to understand the role of responsible AI in value formation and market performance. The analysis revealed that responsible AI – encompassing technical skills, ethical concerns and risk mitigation – is a third-order construct that can promote patient cognitive engagement. This engagement, in turn, positively affects the patient's perceived value and highlights the importance of addressing the ethical and trust components of successful AI deployment [20]. From healthcare professionals' perspectives, perceived value plays a crucial role in the adoption of AI-based technologies. Employee burnout negatively affects adoption; however, after enhancing the perceived value among staff, it was found to reduce burnout and encourage adoption [21]. An experimental study on virtual health assistants demonstrated high-quality direct patient interaction, achieving a 92% accuracy rate in patient query response and an 85% positive feedback rate in satisfaction surveys due to the efficacy of AI techniques [22].

4.5 Non-Empirical Studies

4.5.1 Conceptualisation of AI in Value-Based Healthcare

Numerous non-empirical studies have aimed to establish a conceptual framework for incorporating AI/ML technologies into value-based models. One such protocol worked to investigate the coverage of VBC, patient-centred medicine and personalised medicine (PM) via the systematic review methodology to understand the role of technology in improving healthcare delivery, in which VBC programmes significantly benefit from providing the targeted intervention for high-risk populations. Machine learning algorithms, along with Electronic Health Records (EHR), support population health by identifying individuals at risk for chronic diseases [23].

The majority of the conceptual papers addressed the impact of ML as a catalyst for VBC, ranging from the prediction of hospital readmissions to the automation of home medical equipment for data insights [2]. Artificial intelligence and big data can be used to optimise value-based contracting with the integration of real-world data and ML aspects, such as predictive modelling and outcome assessment [24].

4.5.2 Integration of Patient-Reported Outcome Measures With AI

There is a growing demand to integrate patient-centric data – such as patient-related outcome measures (PROMs) and patient-reported experience measures (PREMs) – with AI systems to deliver this value for patients. From the scoping review protocol findings, there is an identified need for public involvement in developing AI. This will enable ML algorithms to leverage subjective patient feedback, such as pain and functional level. Hence, the patient perspective is vital for the success of digital health applications designed for the self-management of patients within the VBC model [25].

5. Discussion

5.1 Opportunities for AI Adoption and Implementation

5.1.1 Monetary Value of Health Service

Artificial intelligence–powered solutions improve the accuracy of clinical diagnosis, reduce medical errors, prevent unnecessary follow-up tests and generate significant cost savings. This was confirmed by three studies [26],[28],[30]. Trained ML Algorithms can identify a high-cost patient cohort and estimate potential financial implications within value-based models. This has enabled the implementation of targeted interventions on these patient sets, such as the case in chronic disease management programmes [31].

Insights derived from ML can help institutions by providing data on high-risk patients, allowing providers to allocate resources effectively, increasing preventive care efforts and promoting more productive billing strategies for complex patient scenarios. Predictive analytics on patient groups helps healthcare teams deliver cost-effective care, which enhances their leverage in securing better reimbursement rates and contract negotiations [31]. Machine learning models aid healthcare providers with risk-adjusted pricing by incorporating high-risk insurance claims into pricing models. Natural language processing tools assist in extracting and analysing real-world patient-related data from EHR for the quantification of treatment and its financial impact [31]. Artificial intelligence algorithms have been proven to be faster and more accurate for diagnosis. For example, in mammography scans and patient outcome data, AI reduced the false-negative rate from 25% to 15% [32].

Artificial intelligence automates the routing of administrative tasks and processes, such as claims processing, billing and prior authorisation, which reduces the administrative burden. For example, prior authorisation systems powered by AI were revealed to reduce the work queue volume by 22% and save 300 staff hours per month for one institution. Another study found that artificial intelligence enhances hospital operations using predictive analytics for bed management, equipment utilisation and staffing, leading to optimal resource utilisation and reduced overtime rates in the operating room by 21% in one institution [33]. For instance, cancer surgery deep convolutional neural networks reduced the sample analysis time spent by pathologists from 40 min to 3 min without compromising accuracy. Deep convolutional neural networks were found to reduce the false-negative diagnosis of hip fractures from 17% to 9%, leading to cost savings.

Value-based healthcare models strengthen the capability to incentivise providers based on cost outcomes by enhancing data-driven insights, decision-making in real time and predictive capabilities [4].

5.1.2 Quality of Care

Artificial intelligence tools are equipped with health information regarding concerns and treatment approaches. For instance, AI-powered chatbots have been implemented to provide dietary recommendations, smoking cessation and cognitive behavioural therapy [7]. In rehabilitation, wearable devices powered by AI algorithms can suggest personalised exercise regimens, monitor patient progress remotely and provide real-time feedback to patients and physicians [34].

Artificial intelligence, virtual assistants and chatbots improve patient engagement with the provider by simplifying routine tasks using automation. These include scheduling appointments, sending medication reminders and providing personalised medical care and advice [7],[22]. Teleconsultation platforms using AI chatbots can triage and assess patient queries during scheduled appointments and pre-consultation assessments, leading to efficient consultation[22].

Improvements in patient satisfaction are possible through the integration of NLP and reinforcement learning into virtual health assistant–enabled systems to receive and understand patient queries and respond more empathetically[22],[35].

Patient-related outcome measures and PREMs are key metrics for measuring the perceived value of patients. Artificial intelligence aids in the integration and review of patient-generated health data (PGHD) to design and implement personalised and cost-effective patient care. The 'IMPROVE' project was launched to integrate PGHD to facilitate VBHC [3]. Decision support systems using AI can provide recommendations based on evidence-based guidelines, such as IBM Watson for Oncology, with improved accuracy. PathAI Diagnostic Pathology Assistant enhanced the diagnostic capabilities, and Aidoc Radiology AI Imaging reduced reading time for radiologists [36]. This reinforces AI's role as a decision support tool, not as a substitute for human care and interaction [37].

5.1.3 Patient-Centred Care

Artificial intelligence systems are key to tailoring medical care to individual patient needs and characteristics, such as genetics, lifestyle, biomarkers and the environment. This approach moves ahead of the 'one-size-fits-all' approach in healthcare [7],[31]. Disease detection at an early stage is now possible owing to ML capabilities and significant improvements in patient care quality, accessibility and efficiency[22]. In chronic disease management, AI assists in analysing data and recommending treatment plans, which has been proven to be effective in regulating insulin infusion for diabetes patients on continuous glucose monitoring [22]. Personalised communication is possible between patients and providers through AI-powered communication channels, such as patient portals [37].

Artificial intelligence provides real-time, customised information and recommendations, enabling and motivating patients to take better control of their health through enhanced clinical knowledge [7], [22]. For medical providers, AI can analyse medical backgrounds and health information to assist with medical advice and recommendations [37]. Prostheses supported by AI can detect and categorise myoelectric signals to predict movements, improving self-management and reducing training expenditure. This ultimately supports patient autonomy [37].

Artificial intelligence–powered remote monitoring systems, such as wearable devices and sensors, help in the continuous tracking of patient health metrics and alert the provider for any issues [8],[36]. For instance, wearable devices integrated with AI can collect data, track irregularities in heartbeat and notify the user and provider for prompt treatment, which leads to patient safety and the reduction in hospital visits [19]. Therefore, AI plays a predominant role in achieving the quadruple aim of healthcare: improved outcomes, lowered costs, enhanced provider satisfaction and better patient experience [33].

6. Challenges and Barriers of Adoption

6.1 Technical and Data-Related Challenges

Artificial intelligence relies on large volumes of data that should be of high quality and consistent in nature. Artificial intelligence model integrity depends on the validity of its input data, which are often derived from retrospective analyses [33]. Healthcare data are frequently fragmented, inconsistent and siloed, which limits the accuracy and scalability [17]. Major gaps exist in data acquisition, integration and governance within organisations [31],[35]. Current datasets may not represent the varied linguistic and cultural backgrounds that cause gaps in the generalisation of AI systems [33].

Health systems rely on diverse applications, such as EHR, which have varied data formats, standards and terminologies that hinder the implementation of AI solutions. Streaming these systems is a time-consuming, complex and resource-intensive task [26],[38]. Artificial intelligence has proven to be effective in improving diagnosis accuracy; however, its reliability depends on extensive testing and human trials [8],[17],[34],[36],[37],[39].

Most AI Algorithms operate with an opaque underlying mechanism that cannot be understood by the physician, leading to the black box phenomenon, which impacts clinicians' trust and acceptance [2],[16],[19],[33],[39],[41]

Efficiency depends on extensive testing and human trials [17],[34],[36]. Many AI theoretical models require real-world validation to gauge their generalisability. For example, the AI model developed to focus on colorectal cancer lacks generalisability and heterogeneity when considering a wide population, and different cost mechanisms differ by payer. Observational studies generally provide outcomes related to sensitivity and specificity but not the actual clinical impact or net costs [16],[17], [31].

6.2 Ethical and Legal Concerns

The adoption of AI in healthcare requires compliance with regulations such as HIPAA and GDPR to protect patient privacy and data ownership [7],[26]. Any errors in data handling can cause a loss of trust among the public and attract litigation [26]. Defining the responsibility for the potential malfunction of AI systems is a complex task both ethically and legally. With AI-assisted decisions, clinicians must understand the capabilities and limitations of AI systems [22],[26],[33],[34],[39],[42].

Patients are sceptical about adopting AI, demonstrating varying levels of trust and comfort. As humans are the centre of care, patients tend to perceive AI as a decision support tool rather than a substitute for human practitioners [7],[27],[28],[33],[34],[37],[39],[42]. Artificial intelligence cannot replicate human empathy, as non-verbal cues and voice intonation are crucial in

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healthcare delivery, especially in mental health [7],[34],[37],[39].

Poorly designed AI systems or those trained on biased data can exacerbate racial and healthcare disparities. When utilised to estimate costs and healthcare utilisation, such AI systems can lead to inequality and reinforce broader structural inequalities [27],[33],[34],[35],[37].

6.3 Human and Professional Challenges

Owing to a lack of a comprehensive understanding of AI principles, healthcare professionals show resistance to adopting AI systems. Resistance is often triggered by job security and workflow changes [7],[26],[33],[37],[39],[40],[42]. Physicians expect complete transparency to understand the phenomena and underlying thought process to arrive at a decision that is counterintuitive to the black box nature of AI [34],[42].

Artificial intelligence driven by automation might not only cause a reduction in clinician skills and lead to 'deskilling' but also increase workload and burnout if not properly implemented [21],[26],[33],[37],[42]. Artificial intelligence technology implementation requires training and resource allocation to ensure safety and productivity [7],[17],[26],[33],[37]. There is a need to start introducing literacy- and concept-specific AI at the undergraduate level to support professional development [7].

6.4 Economic and Implementation Hurdles

Artificial intelligence technologies require upfront capital investment in the form of infrastructure, data storage, skilled professionals and computational power [7],[33]. Integrating AI into existing applications, such as EHR, is costly and further increases the expenses due to maintenance, continuous updates and the regular training of AI models [17].

Existing regulatory frameworks are inadequate in governing the rapid development of AI technologies [22]. Strict regulatory requirements are often difficult to comply with, and guidelines for real-world AI use cases remain underdeveloped [8],[22],[37],[42]. The official ownership of existing AI platforms also lacks peer-reviewed literature for assessment [27].

7. Limitations

A literature search revealed numerous healthcare use cases in which AI technology and VBHC are applied as broad concepts. To address this challenge, we considered the conceptual attributes of VBHC – the monetary value of health services, quality of care and PCC – based on a conceptual analysis[29].

Although the study adds valuable contributions to the literature review, it has a set of limitations. The study protocol was not prospectively registered in the databases such as Open Science Framework. The inclusion of literature was restricted to open-access articles published between 2020 and 2025, and non-English language studies were excluded from the review. The shortlisted papers are not completely empirical in nature and contain a mix of reviews, case studies and original studies.

Most studies focus on high-income countries or specific regions, which challenges the generalisability of the findings. This geographical concentration limits external validity and ignores regional disparities in AI adoption [2],[15],[17],[18],[20].

8. Future Directions

Future research should focus on developing transparent and understandable AI models (XAI). Algorithms that display a black box nature will hinder trust among clinicians, leading to poor adoption. Clinicians should be able to access the underlying decision-making process [8],[16],[26],[28],[42]. Healthcare administrators and policymakers should mandate the XAI requirements during the procurement and vendor-selection process for algorithmic transparency [20]. Artificial intelligence model validation must be expanded across different populations to test its effectiveness and generalisability [36]. This involves performance testing against standard metrics for scalability and evaluation across various medical domains [16]. Ongoing work is crucial for analysing and investigating data bias and managing algorithms to avoid racial and gender differences [34]. There should be fairness and inclusivity in training datasets for equitable care delivery [20], [34]. The seamless integration of AI solutions with EHR is essential for improving the ML model performance in predictive analytics and patient engagement [31].

The cost–benefit analysis of AI models is crucial for guaranteeing improved economic impact and better return on investment for healthcare providers [33], [36]. Longitudinal studies are necessary to track clinical and patient outcomes over the years, providing sustained, long-term benefits of VBHC models and AI-based PM [20],[31].

Improving user experience and accessibility related to AI-driven applications will promote their widespread adoption by patients and healthcare providers [36]. Further studies can explore the feasibility, perceived utility and acceptability of adopting NLP and ML to assess coordinated care and unmet social needs from the perspectives of patients, providers and healthcare administrators [27].

9. Conclusion

Artificial intelligence technologies show promise for enhancing the implementation and adoption of VBHC models. With the integration of digital health technologies, AI can transform healthcare outcomes for patients. In VBHC, AI can demonstrate its impact on patient-centred care, quality of care and monetary value through personalised care, clinical outcome management and cost measurement. The value of AI in healthcare can be realised with a structured framework of governance at the national level, and leadership involvement in driving the AI-based VBHC programmes at the facility level. The responsibility lies with the hospital leadership and the Information Technology department to educate the hospital staff on the impact of AI-based solutions on the clinical and operational processes. However, AI has limitations in terms of implementation and adoption among healthcare professionals. Lack of transparency in clinical judgements and the high costs associated with the implementation of AI models are creating barriers to progress. The current literature is more skewed towards the conceptual frameworks rather than long term empirical evidence. Additionally, there is a growing demand for AI governance and ethical principles to ensure the fair use of AI in VBHC. This review aims to highlight AI-based technologies in advancing Value-Based Healthcare, and there is a need for long-term empirical evidence and transparency to appreciate the proven clinical "value."

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