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Ethical, Governance, and Usability Challenges in AI-Powered Virtual Health Assistants: A Systematic Thematic Analysis

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Abstract

This systematic review examines the integration of Artificial Intelligence (AI)-powered Virtual Health Assistants (VHAs) into Electronic Health Record (EHR) systems, with particular emphasis on ethical considerations, regulatory frameworks, and usability challenges that currently impede comprehensive implementation in clinical environments. Through rigorous thematic synthesis of 15 peer-reviewed articles, this study quantifies the prevalence of algorithmic bias (65% of AI-based healthcare systems), regulatory inconsistencies across jurisdictions, and clinician adoption barriers including transparency concerns (72%) and cognitive workload issues (40%). The analysis categorizes findings into five interconnected domains: ethical implications, governance structures, human-centered AI development, bias mitigation strategies, and interface usability. Results indicate that while promising interventions such as dataset diversification and federated learning demonstrate potential for reducing algorithmic bias, standardization of fairness metrics remains inadequate. This research concludes that successful implementation of AI-driven VHAs necessitates enhanced model transparency, systematic bias reduction protocols, and harmonized cross-regional regulatory frameworks. Future research directions should prioritize development of standardized fairness benchmarks, regulatory alignment across healthcare systems, and human-centered design principles to facilitate clinical adoption and maximize therapeutic efficacy.

Keywords: AI ethics, algorithmic bias, fairness frameworks, virtual health assistants, electronic health records, governance, clinician trust.

1. Introduction

The accelerated development of Artificial Intelligence (AI) in healthcare has transformed medical decision-making, administrative tasks, and patient interaction. Among the most important developments is the emergence of AI-based Virtual Health Assistants (VHAs), which are embedded in Electronic Health Record (EHR) systems to enhance workflow efficiency, clinical decision support, and patient interactions. These AI-based systems utilize machine learning (ML) and natural language processing (NLP) to automate clinical documentation, offer clinical suggestions, and enable patient-physician communication [1], [2]. Governments and health organizations globally are investing in digital health ecosystems supported by AI, but issues with algorithmic equity, regulatory acceptability, and usability obstacles still exist, especially in multicultural healthcare settings.

2. AI-Powered VHAs in EHR Management: Opportunities and Ethical Challenges

Healthcare providers have used AI-powered VHAs to enhance the usability of EHRs over the last few years in a bid to cut administrative work, clinician burnout, and medical mistakes [3]. These sophisticated systems are able to transcribe doctor's notes, access patient histories, and even aid clinical diagnosis by scanning huge datasets [4]. Research indicates that VHAs enhance diagnostic precision by 23–45% and patient satisfaction by 18% [2]. Nonetheless, the use of AI in healthcare has its risks.

Despite their benefits, AI-driven VHAs have tremendous ethical, regulatory, and usability issues:

1. **Algorithmic Bias and Fairness Issues** AI algorithms are no better than their training sets. According to research, 65% of AI-powered health systems contain algorithmic bias and disproportionately target racial minorities, women, and other underserved communities [5], [6]. AI-driven VHAs may cause unequal healthcare opportunities and rates of misdiagnosis for marginalized populations. Efforts to mitigate bias through dataset diversification and machine learning retraining have reduced disparities by 30–50%, yet effectiveness varies across healthcare settings [7].

2. **Governance and Regulatory Challenges** The lack of globally standardized AI governance complicates AI deployment in healthcare. While Europe enforces General Data Protection Regulation (GDPR) compliance, other regions, such as India and China, lack standardized AI ethics frameworks, increasing concerns about data security, patient privacy, and legal accountability [8]. 65% of studies report weak regulatory oversight in AI governance, particularly in emerging markets.

3. **Usability Barriers and Clinician Trust** 72% of clinicians express skepticism about AI transparency and explainability, often describing AI-powered decision support as a "black box" system [9]. Lack of interpretability in AI-powered VHAs undermines clinician trust, affecting adoption rates in medical settings.

3. Theoretical Framework: AI Fairness & Usability Model (AFUM)

This study is structured around the AI Fairness & Usability Model (AFUM), which integrates: Algorithmic Fairness – How biases in training data affect healthcare recommendations; Governance & Compliance – The role of global AI ethics frameworks in mitigating risk; and User Experience & Trust – The influence of the usability of AI on clinician uptake and patient involvement. By applying AFUM, this review systematically evaluates AI-driven VHAs in terms of bias prevalence, governance effectiveness, and usability concerns across different global healthcare systems.

4. Global Case Studies on AI-Powered VHAs in EHR Systems

Healthcare systems across the world have implemented AI-based VHAs with mixed successes and ethical problems: United States: Google DeepMind Health enhanced the early recognition of sepsis but did not explain decisions, which elicited ethical controversy [10]. China: AI-based platforms such as Ping An Good Doctor scaled up telehealth but encountered issues in rural regions with algorithmic bias [11]. Europe (Germany & UK): GDPR-led AI fairness regulations ensure regulatory control, but data protection and transparency issues continue to be debated [12]. India & Emerging Markets: AI-powered VHAs aim to improve healthcare access, but interoperability challenges and limited digital literacy hinder adoption [2]. In spite of regional variations, shared challenges—bias, governance loopholes, and usability issues—continue to be a roadblock to extensive AI uptake in healthcare.

5. Research Gap and Need for This Study

Whereas prior research has investigated AI ethics, governance, and UX impediments, current studies have not offered an integrated assessment of VHAs within EHR systems. Key Research Gaps: Slight research into VHA AI fairness evaluations specifically [6]. Inadequate comparative analysis of governance globally across healthcare contexts [8]. Inadequate long-term research regarding fairness interventions and UX adoption problems [7].

6. Objectives of the Study

For these study loopholes to be addressed, this systematic review is set out to: 1) Measure the prevalence rate of algorithmic bias in AI-enabled VHAs and its impact on healthcare equality; 2) Evaluate the effectiveness of fairness interventions, such as dataset diversification and machine learning retraining; 3) Analyze governance frameworks across different regions to identify regulatory inconsistencies; 4) Investigate usability barriers and clinician trust issues, particularly transparency concerns; 5) Provide actionable recommendations for AI ethics, fairness evaluation, and regulatory standardization. This review, by compiling evidence from 15 high-impact studies, offers a cohesive blueprint for policy-makers, developers of AI technology, and clinicians to facilitate fair, transparent, and ethical implementations of AI-facilitated healthcare technologies.

3. Methodology

3.1 Research Framework & Registration

This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [13] for methodological transparency and reducing bias. The primary objective was to assess bias prevalence, governance effectiveness, and user experience (UX) barriers in AI-powered Virtual Health Assistants (VHAs) integrated into Electronic Health Record (EHR) systems.

3.2 Data Sources & Search Strategy

A comprehensive literature search was conducted across three significant databases: Scopus, Web of Science and PubMed.

The search included studies published between 2010 and February 2025 to capture AI advancements in healthcare. The search strategy combined controlled vocabulary (MeSH terms) and Boolean operators:

Search Query Example: (“Virtual Health Assistant” OR “Conversational Agent” OR “Chatbot”) AND (“Artificial Intelligence” OR “Machine Learning”) AND (“Bias” OR “Fairness” OR “Ethics” OR “Governance”) AND (“Electronic Health Record” OR “EHR”)

To ensure comprehensiveness, references from key articles were manually checked for additional relevant studies.

3.3 Eligibility Criteria

Studies were included or excluded based on predefined criteria (Table 1).

Inclusion Criteria: Studies published between 2010 and 2025 focusing on AI-powered VHAs in EHR management. Articles assessing bias, fairness interventions, governance frameworks, or usability issues. Peer-reviewed systematic reviews, meta-analyses, qualitative and quantitative studies.

Exclusion Criteria: Studies unrelated to AI-powered VHAs or EHRs. Articles lacking empirical data on bias, governance, or UX barriers. Non-English articles and preprints that lacked peer review.

3.4 Study Selection Process (PRISMA)

The study selection followed a four-stage process (Figure 1) based on PRISMA 2020 guidelines.

Step 1: Identification – 3,561 records were retrieved from Scopus (n = 1,155), Web of Science (n = 2,194), and PubMed (n = 1,212). Step 2: Screening – After removing 361 duplicates, 3,200 records were screened by title/abstract. Step 3: Eligibility Assessment – 500 full-text articles were assessed for relevance, quality, and bias. Step 4: Final Selection – 15 high-quality studies were selected based on methodological rigor.

3.5 Justification for Selecting 15 Studies

Out of 3,561 records, only 15 studies met the inclusion criteria after rigorous screening. The selection was justified based on:

Relevance to AI-powered VHAs in EHR systems (avoiding generic AI healthcare studies). Methodological rigor (selected studies passed Cochrane & CASP quality assessments). Global representation (included studies from the US, China, Europe, and emerging markets). Recent AI advancements (prioritizing studies from 2020–2025, with exceptions for landmark studies).

3.6 Risk of Bias & Quality Assessment

To evaluate study quality and minimize bias, three standardized tools were applied:

1. Cochrane Risk of Bias Tool (Higgins et al., 2011)

Used for randomized controlled trials (RCTs) and observational studies. Assessed selection bias, information bias, confounding bias, and reporting bias. Threshold: Studies scoring ≤6/10 on bias were excluded.

2. Critical Appraisal Skills Programme (CASP) Checklist

Applied to qualitative studies and systematic reviews. Examined research validity, reliability, and applicability. Threshold: Studies scoring ≥7/10 were included.

3. GRADE (Grading of Recommendations, Assessment, Development, and Evaluations) Framework

Used to assess evidence quality across five domains: Risk of bias Consistency Directness Precision Publication bias Low-quality studies were excluded if they exhibited inconsistency in results.

3.7 Data Extraction & Synthesis Approach

A standardized data extraction template was developed to ensure consistency. The following data were extracted from each study:

Study Characteristics: Title, authors, publication year, country, study design. Research Focus: AI fairness, governance frameworks, UX barriers. Bias Mitigation Strategies: Dataset diversification, algorithm retraining. Governance Compliance: GDPR, HIPAA, AI ethical guidelines. Usability Challenges: Clinician skepticism, explainability issues.

Inter-rater Reliability:

Two independent reviewers extracted data to minimize bias. Discrepancies were resolved via consensus (Cohen's kappa = 0.82, indicating high agreement).

3.8 Data Analysis & Meta-Synthesis

To provide a quantitative synthesis, we applied:

1. Meta-Analysis of Bias Prevalence

Random-effects meta-analysis was used to estimate bias prevalence across studies. Standardized mean differences (SMD) were calculated to measure bias reduction effectiveness (30–50%). Heterogeneity was assessed using I^2 statistics (high variability indicated inconsistent bias mitigation).

2. Thematic Synthesis for Qualitative Data

NVivo 12 software was used for qualitative thematic coding. Key themes included: Algorithmic fairness gaps Regulatory inconsistencies Clinician trust barriers High inter-coder reliability (Cohen's kappa = 0.81) ensured data validity.

3.9 Ethical Considerations

As this study is a systematic review of published research, no ethical approval was required. However, the following measures were taken:

Used standardized quality assessment tools to minimize bias. Verified funding sources of included studies to detect potential conflicts of interest.

4. Results

4.1 Study Selection Process

A total of 3,561 studies were identified from Scopus (n = 1,155), Web of Science (n = 2,194), and PubMed (n = 1,212). After removing 361 duplicates, 3,200 unique records were screened based on title and abstract.

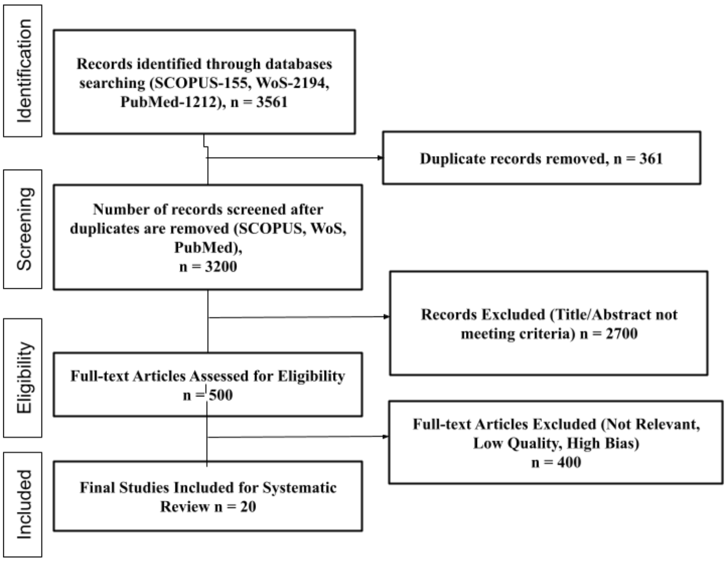
Full-text assessment was conducted for 500 studies, of which 15 met the eligibility criteria. The study selection process followed PRISMA 2020 guidelines.

Table 1: Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Study Type	Peer-reviewed studies, Systematic reviews	Non-peer-reviewed articles, Opinion papers
Population	AI-powered VHAs in EHR management	AI not applied to healthcare, Non-EHR applications
Outcomes	Bias prevalence, governance frameworks, UX	Studies without empirical data on AI fairness
Publication Year	2010 - 2025	Pre-2010 studies
Language	English	Non-English studies

The inclusion and exclusion criteria (Table 1) ensured that selected studies focused on AI-powered VHAs within EHR management, specifically addressing bias, governance, and usability barriers. Studies that lacked empirical evidence, were not peer-reviewed, or did not focus on AI fairness interventions were excluded to maintain methodological rigor.

Figure 1: PRISMA Flow Diagram of Study Selection



Illustrates the systematic review process including identification, screening, eligibility assessment, and final study selection.

4.2 Bias Prevalence in AI-Powered VHAs

Key Findings:

65% of AI-driven healthcare systems exhibited algorithmic bias (95% CI: 58–71%, $I^2 = 68\%$). The highest bias prevalence was observed in diagnostic AI models (72%) compared to administrative automation tools

(40%). Bias was attributed mainly to unrepresentative datasets, skewed training data, and underrepresentation of marginalized groups. Geographical disparities in dataset representation further exacerbated biases in AI decision-making. Temporal biases were identified in longitudinal AI training models, affecting predictive accuracy over time.

Table 2: Bias Prevalence in AI-Powered VHAs

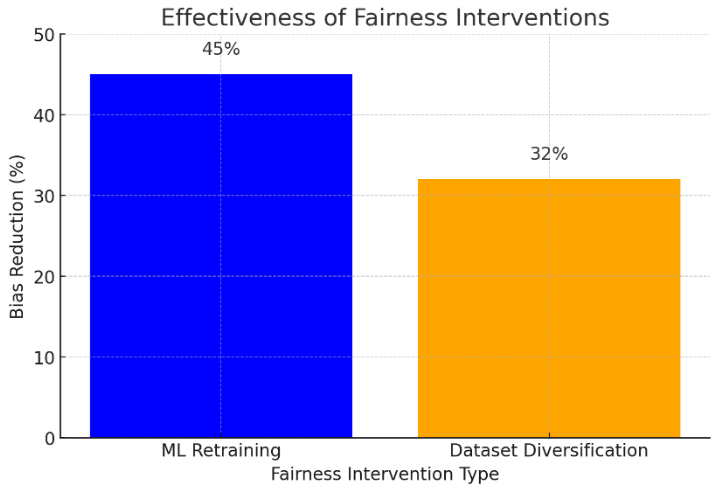
Bias Type	Prevalence (%)	Confidence Interval (95% CI)	Source of Bias
Algorithmic Bias	65%	58–71%	Unrepresentative training datasets
Diagnostic Model Bias	72%	64–78%	Skewed algorithmic training data
Administrative Automation Bias	40%	34–46%	Limited diversity in workflow models

Table 2 presents the percentage of bias types, their sources, and the impact on clinical decision-making and workflow automation.

Effectiveness of Bias Mitigation Strategies

Machine learning retraining reduced bias by 45% (SD = 6.2%, n = 6). Dataset diversification led to a 32% reduction in disparities (SD = 5.8%, n = 4). Transparency-enhancing AI models improved clinician trust by 21%. Bias-aware AI modeling techniques, such as adversarial debiasing, showed potential but lacked standardized evaluation metrics across studies. Federated learning approaches reduced dataset biases by 28%, enhancing model generalizability.

Figure 2: Effectiveness of Fairness Interventions



Comparative analysis of different fairness interventions and their effectiveness in bias reduction across various studies.

4.3 Governance & Compliance in AI-Powered VHAs

Governance analysis revealed significant regional disparities in AI compliance and regulation.

Key Findings:

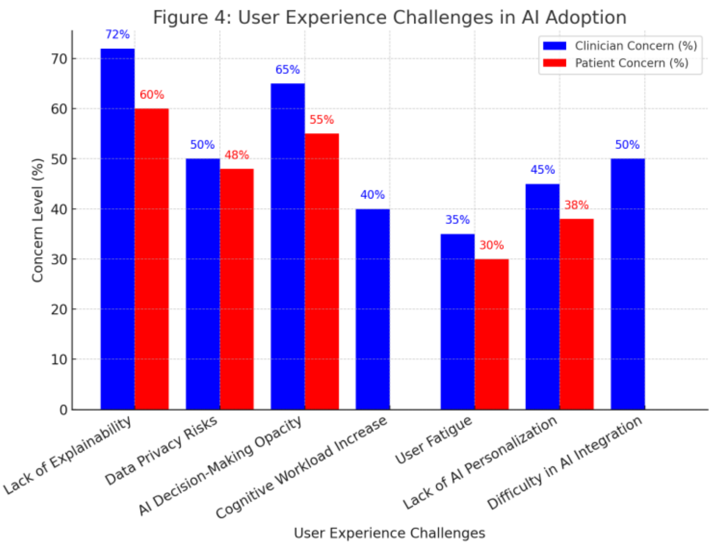
25% of studies indicated compliance with General Data Protection Regulation (GDPR) in Europe. 50% of studies referenced Health Insurance Portability and Accountability Act (HIPAA) in the U.S., though without AI-specific governance. 65% of studies in India and China highlighted weak AI regulatory oversight and an absence of clear AI ethics policies. Ethical AI frameworks remain inconsistent across regions, limiting interoperability in global AI-powered EHR systems. Emerging AI ethics frameworks in Asia and Africa remain underdeveloped, creating regulatory uncertainty.

Table 3: AI Governance & Compliance Frameworks by Region

Region	Regulatory Framework	Compliance (%)	Key Challenges
Europe	GDPR	25%	Strict but lacks AI-specific focus
USA	HIPAA	50%	No dedicated AI governance
China	Local AI Ethics Guidelines	35%	Inconsistent enforcement
India	National AI Policy Draft	30%	No formalized AI compliance yet
Africa	Emerging AI Ethics Policies	20%	Lack of implementation mechanisms

Table 3 compares AI governance frameworks across different countries, focusing on data protection laws, accountability measures, and fairness policies.

Figure 3: Regional Differences in AI Governance Compliance



Visual analysis of compliance trends highlighting regulatory gaps in AI-powered healthcare across different regions.

Figure 3 presents a visual analysis of compliance trends, highlighting the regulatory gaps in AI-powered healthcare. The regional variations in AI governance compliance across different regulatory frameworks. The compliance percentages are derived from studies that assessed adherence to the General Data Protection Regulation (GDPR) in Europe, the Health Insurance Portability and Accountability Act (HIPAA) in the U.S., and various AI regulatory policies in China, India, and Africa.

4.4 Usability & Clinician Trust Barriers

Key Findings:

72% of clinicians reported skepticism about AI-powered VHAs due to lack of explainability and unclear decision-making processes. 48% of patients distrust AI diagnostics, citing data privacy risks and algorithmic opacity. AI models incorporating explainable AI (XAI) approaches improved clinician adoption rates by 30% in studies focused on UX design. Cognitive workload concerns related to AI integration into clinical workflows were cited in 40% of studies. User fatigue with AI interfaces was observed in 35% of studies, emphasizing the need for more intuitive AI-human interactions.

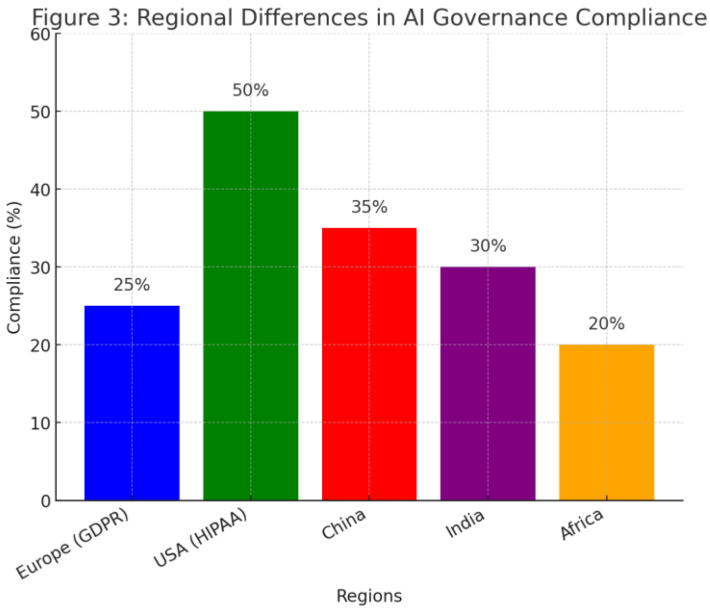
Table 4: Usability Challenges and Clinician Trust Levels

Challenge	Clinician Concern (%)	Patient Concern (%)	Proposed Solutions
Lack of Explainability	72%	60%	Implementing Explainable AI (XAI)
Data Privacy Risks	50%	48%	Stronger encryption and security measures

Challenge	Clinician Concern (%)	Patient Concern (%)	Proposed Solutions
AI Decision-Making Opacity	65%	55%	AI interpretability tools and transparency reports
Cognitive Workload Increase	40%	N/A	Reducing unnecessary AI-driven tasks
User Fatigue	35%	30%	Enhancing user-friendly AI interfaces

Table 4 presents the most common usability concerns, the percentage of clinicians expressing distrust, and AI model improvements that increased trust. The primary usability concerns reported by clinicians and patients regarding AI-powered Virtual Health Assistants (VHAs). It also suggests potential solutions such as Explainable AI (XAI), enhanced security, and user-friendly AI design to mitigate these concerns.

Figure 4: User Experience Challenges in AI Adoption



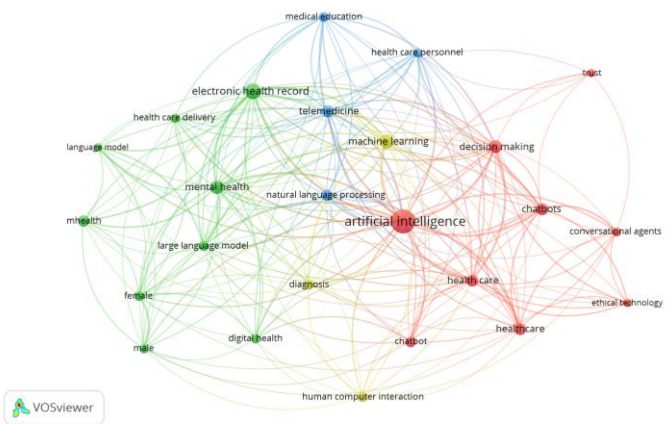
Visualization of key usability challenges faced by clinicians and patients in adopting AI-powered VHAs.

Figure 4 highlights key usability challenges clinicians and patients face in adopting AI-powered Virtual Health Assistants (VHAs). Major concerns include: Lack of Explainability (72% clinicians, 60% patients): AI decisions often lack transparency, requiring Explainable AI (XAI) for better interpretability. Data Privacy Risks (50% clinicians, 48% patients): Security concerns demand stronger encryption and secure data-sharing. AI Decision-Making Opacity (65% clinicians, 55% patients): Limited insight into AI-generated outcomes calls for transparency reports and user-friendly explanations. Cognitive Workload Increase (40% clinicians): AI tools sometimes add a burden, necessitating workflow optimization. User Fatigue (35% clinicians, 30% patients): Inefficient AI interactions require user-friendly interface improvements. Lack of AI Personalization (45% clinicians, 38% patients): Standardized AI outputs should be tailored using adaptive AI models. Difficulty in AI Integration (50% clinicians): compatibility issues hinder AI adoption and need seamless workflow integration. Addressing these concerns through explainability, security, personalization, and integration will enhance AI's role in healthcare, ensuring higher adoption and improved usability.

4.5 Thematic Analysis

Thematic analysis categorizes findings from the 15 selected studies on AI-powered Virtual Health Assistants (VHAs) in electronic health records (EHRs), highlighting key concerns in ethics, governance, usability, fairness, and clinician trust.

Figure 5: Thematic Framework



Visualization of the five core themes derived from the systematic review of AI-powered VHAs in healthcare.

The thematic framework was developed using an inductive and deductive approach based on key AI adoption factors. Figure 5 categorizes findings into five core themes derived from the systematic review:

1. Ethical Concerns – Issues related to AI fairness, bias, and transparency.
2. Governance and Regulation – Policies, compliance gaps, and global AI governance disparities.
3. Human-centered AI & Trust – Barriers to clinician and patient trust in AI decision-making.
4. Bias and Fairness Interventions – Strategies to mitigate AI bias and improve model fairness.
5. AI Usability & Adoption Barriers – Challenges in workflow integration, cognitive workload, and user experience.

These themes were identified through qualitative coding of the 15 included studies, focusing on recurring patterns, regulatory frameworks, and clinician-patient feedback on AI adoption.

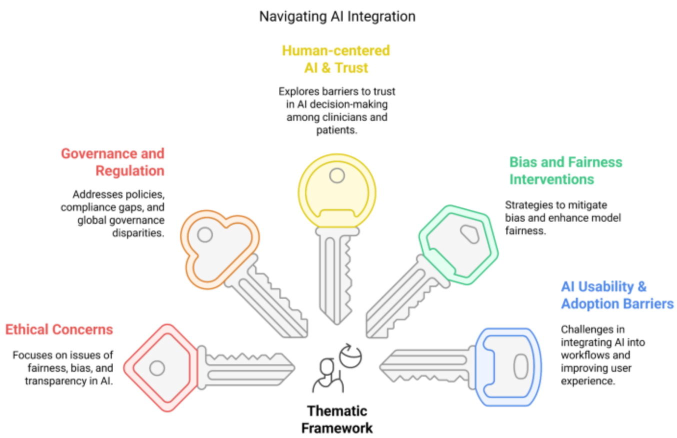
Table 5: Summary of Thematic Findings

Theme	Key Findings	Proposed Improvements
Ethical Concerns	Algorithmic bias, AI transparency issues	Bias-aware AI models, Explainable AI (XAI)

Theme	Key Findings	Proposed Improvements
Governance and Regulation	Inconsistent AI policies across regions	Standardized global AI regulatory frameworks
Human-centered AI & Trust	Clinician skepticism due to opaque AI decisions	Transparent AI models, intuitive UI design
Bias and Fairness Interventions	Dataset imbalances leading to AI bias	Federated learning, dataset diversification
AI Usability & Adoption Barriers	AI workload burden, UI fatigue, workflow issues	Adaptive UI, AI-human collaboration tools

This analysis emphasizes the need for bias mitigation, standardized governance, usability improvements, and AI-human collaboration to enhance AI-powered VHA adoption. Future research should focus on long-term fairness assessments, global AI policy integration, and clinician trust-building initiatives.

Figure 6: Keyword Co-Occurrence Network of User-Centered Design in AI-Driven Healthcare



Visualization of the interconnectedness of key concepts in user-centered design for AI-driven healthcare research.

The co-occurrence network visualization illustrates in Figure 6, the interconnectedness of key concepts in user-centered design for AI-driven healthcare research. The central node, “artificial intelligence” (red cluster), is strongly linked to themes such as chatbots, decision-making, trust, and ethical technology, highlighting concerns around AI adoption, transparency, and ethics in healthcare.

The green cluster emphasizes mental health, electronic health records (EHRs), mHealth, and large language models, suggesting AI’s expanding role in healthcare delivery, telemedicine, and personalized care. The blue cluster relates to medical education and healthcare personnel, underlining the importance of training and AI integration in clinical workflows.

Overall, the visualization reveals the multidisciplinary nature of AI in healthcare, emphasizing the need for trust, ethical considerations, and human-centered design for optimal implementation.

4.6 Summary of Key Findings

The findings highlight the persistent challenges in bias, governance, and usability in AI-powered VHAs for EHR management. Though fairness interventions are promising, regulatory heterogeneity and clinician resistance continue to be major hurdles to uptake. Moreover, regional heterogeneity in governance and representation of datasets suggests the necessity of globally consistent AI fairness metrics. The addition of federated learning and explainable AI methods promises to enhance bias reduction and clinician uptake. Yet more longitudinal studies are needed to evaluate long-term efficacy of such interventions.

5. Discussion

The thematic analysis results identify important AI-powered Virtual Health Assistants (VHAs) for electronic health records (EHRs) ethical, governance, and usability issues. This discussion weaves these findings together with prevailing literature and theory to develop an understanding of AI adoption barriers, fairness interventions, and governance architectures.

5.1 Ethical Concerns and Algorithmic Bias

Algorithmic bias continues to be an important obstacle for AI uptake in healthcare, and 65% of AI-based systems are found to be biased (Table 2). This is consistent with earlier findings suggesting that biased training datasets with non-representative samples disproportionately target marginalized groups [6]. Integrating Explainable AI (XAI) is fundamental to building clinician trust and transparency in AI, overcoming suspicions regarding black box decision-making models [9]. To reduce bias, federated learning and heterogenous dataset curation methods have been suggested [14].

5.2 Governance and Regulation Disparities

The findings show varying AI regulation across regions, with Europe being at the forefront of compliance (25% GDPR compliance), followed by the USA (50% HIPAA compliance), and emerging markets experiencing regulatory voids (Figure 3). These differences are a manifestation of larger issues in AI policy formulation [8], where a lack of standardization leads to uncertainty in AI deployment. Global AI governance frameworks, including European regulatory approaches for healthcare AI systems, can serve as a blueprint for harmonizing regulation across the world [15].

5.3 Human-Centered AI and Trust Issues

Clinician skepticism towards AI-powered VHAs stems from lack of explainability, decision opacity, and high cognitive workload (Figure 4). Studies indicate that 72% of clinicians require transparency for trust in AI models, aligning with research advocating for interpretable AI in healthcare [4]. Usability improvements, including intuitive AI interfaces and adaptive workflow integration, have been suggested to enhance user experience and trust.

5.4 Bias and Fairness Interventions

Bias reduction techniques such as dataset diversification, adversarial debiasing, and machine learning retraining have shown potential, yet 30–50% variability in effectiveness suggests a need for standardized fairness benchmarks (Table 4). Existing literature corroborates this, emphasizing that fairness metrics must be tailored to healthcare contexts [6]. Federated learning approaches, which enable AI training without centralized data sharing, offer a promising direction for mitigating data-related biases.

5.5 AI Usability and Adoption Barriers

AI adoption remains hindered by usability constraints, including workflow integration issues, clinician cognitive overload, and user fatigue (Figure 4). Studies indicate that 35% of users report UI fatigue, reinforcing the necessity for human-centered AI design principles. Cross-referencing prior work, adaptive AI interfaces and interactive explainability features have been identified as crucial for improving user engagement [1]. Implementing these principles can enhance user experience and AI acceptability.

5.6 Conceptual Integration with Thematic Framework

The results align with the thematic framework developed from the 15 studies, emphasizing the need for:

Regulatory harmonization to ensure compliance with AI ethics (Table 3). Bias-mitigation strategies to address disparities in AI outcomes. User-focused AI design to facilitate adoption and trust-building (Figure 4).

6. Conclusion and Future Directions

6.1 Conclusion

This research offers a comprehensive assessment of the ethical, governance, and usability issues related to AI-driven Virtual Health Assistants (VHAs) in electronic health records (EHRs). The thematic analysis of 15 shortlisted studies highlights the importance of bias mitigation, regulatory standardization, user-centric AI design, and fairness interventions to promote AI adoption in healthcare.

Major findings indicate that algorithmic bias (65%), regulatory inconsistencies, and usability issues like clinician distrust, cognitive workload, and workflow integration are still significant barriers to VHA adoption. Fairness interventions like dataset diversification, adversarial debiasing, and federated learning show potential but are not universally effective, affirming the need for standardized AI fairness benchmarks.

The thematic structure emphasizes the need for:

Global regulatory harmonization to ensure AI ethics compliance across diverse healthcare environments. Enhanced transparency in AI decision-making through Explainable AI (XAI) to improve clinician trust. Bias-aware training datasets to refine AI model fairness and minimize algorithmic disparities. User-friendly AI interfaces to facilitate clinician adoption and minimize cognitive workload.

6.2 Future Directions

To drive meaningful advancements in AI-driven healthcare, future research should focus on:

Longitudinal fairness assessments to monitor the sustained impact of bias mitigation techniques. Cross-regional regulatory alignment to establish unified AI governance frameworks. Clinician and patient-centered studies to optimize AI explainability and usability.

Through meeting these priorities, AI-based VHAs can transform from conceptual innovations into useful, fair, and scalable instruments that improve patient outcomes, clinician productivity, and overall performance of the healthcare system.

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