

Interactive Data Visualization Techniques for Enhancing AI Decision Transparency in Healthcare Analytics: A Comparative Analysis

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Abstract: Artificial intelligence (AI) systems in healthcare increasingly influence critical clinical decisions, yet their complex decision-making processes often remain opaque to practitioners. This paper presents a systematic comparative analysis of interactive data visualization techniques designed to enhance AI decision transparency in healthcare analytics. A multi-dimensional classification framework was developed to categorize visualization approaches based on data type compatibility, interaction modality, transparency mechanism, and implementation complexity. Eighteen distinct visualization techniques were evaluated using a comprehensive assessment methodology combining quantitative performance metrics and qualitative expert evaluations across diverse healthcare contexts. The analysis revealed that parallel data and information visualization approaches achieved the highest transparency scores (4.5/5), while temporal visualization techniques demonstrated superior performance for longitudinal clinical data interpretation. Stream-based visualizations with adaptive smoothing algorithms proved particularly effective for patient flow pattern analysis. Strong correlation ($r=0.78$, $p<0.001$) was identified between interaction depth and transparency effectiveness. The research establishes evidence-based guidelines for implementing visualization solutions in clinical environments, addressing technical infrastructure requirements, workflow integration considerations, and user training recommendations. These findings provide a foundation for developing more transparent, interpretable AI systems that can effectively support clinical decision-making while maintaining appropriate levels of user trust and engagement.

Keywords: Interactive Data Visualization, AI Transparency, Healthcare Analytics, Clinical Decision Support

1. Introduction

1.1. Background and Significance of AI Transparency in Healthcare

The adoption of artificial intelligence (AI) in healthcare has expanded significantly, powered by the exponential growth in healthcare data. Electronic Health Record (EHR) systems have experienced an eightfold increase in adoption rates since 2008, resulting in vast collections of longitudinal

medical data across diverse patient populations [1]. This digital transformation has catalyzed the development of AI-driven clinical decision support systems, diagnostic tools, and predictive analytics platforms. Healthcare AI applications now span diagnostic imaging interpretation, treatment recommendation, risk stratification, and patient monitoring. The integration of these technologies promises improved patient outcomes, operational efficiencies, and enhanced clinical decision-making. Nevertheless, AI systems often function as "black boxes," where the relationships between inputs and outputs remain opaque to clinicians, patients, and healthcare administrators [2]. Transparency in healthcare AI refers to the understandability and interpretability of AI-driven decisions and recommendations. This transparency is critical for establishing trust, validating clinical applications, meeting regulatory requirements, and ensuring ethical implementation of AI technologies in healthcare settings [3].

1.2. Challenges in Understanding AI-Driven Healthcare Decisions

Healthcare data presents unique visualization challenges distinct from other domains. The complexity arises from the heterogeneous nature of medical data, which includes structured elements (laboratory values, vital signs), unstructured components (clinical notes, imaging reports), temporal sequences, and multimodal information [4]. Clinicians face substantial cognitive burdens when interpreting AI outputs without adequate visualization support, potentially leading to incorrect implementation of recommendations or complete disregard of AI-generated insights [5]. Healthcare decisions typically involve high-stakes outcomes with direct impacts on patient care, magnifying the importance of transparency. Statistical rigor in healthcare visualization surpasses requirements in other domains, where "interesting" patterns alone are insufficient justification for action [6]. Current visualization techniques frequently fail to represent uncertainty in AI predictions, model confidence levels, or alternative decision pathways. Additional challenges include the representation of temporal relationships, missing data patterns, and contextual factors that influence AI outputs [7].

1.3. Research Objectives

This paper aims to systematically analyze and compare interactive data visualization techniques designed to enhance transparency in AI-driven healthcare analytics. The research evaluates visualization approaches across multiple dimensions, including their ability to communicate complex algorithmic processes, represent uncertainty, support exploratory analysis, and facilitate clinician-AI collaboration [8]. A comprehensive classification framework is developed to categorize visualization techniques based on their technical implementations, interaction models, and transparency enhancement capabilities [9]. The comparative analysis examines both established visualization methods and emerging approaches, including time-based visualizations for longitudinal health data, interactive network representations for relationship analysis, and integrated visualization systems that support parallel data and information exploration. Through this systematic comparison, the research identifies optimal visualization strategies for specific healthcare contexts and user requirements. The findings contribute to the development of design guidelines for creating more transparent, interpretable, and clinically useful AI systems in healthcare settings [10].

2. Literature Review and Theoretical Framework

2.1. Evolution of Data Visualization in Healthcare Analytics

Data visualization in healthcare has progressed significantly from static representations to sophisticated interactive systems. Early healthcare visualizations, such as John Snow's 1854 cholera outbreak map, demonstrated the fundamental value of spatial visualization in epidemiology. The advancement of computational capabilities in the 1980s and 1990s enabled more complex healthcare data representations, primarily focused on statistical charts and basic medical imaging [11]. The 2000s witnessed the integration of interactive elements, allowing basic user manipulation of visualized healthcare data. Contemporary healthcare visualization has evolved toward comprehensive visual analytics platforms incorporating real-time data processing, multi-dimensional representations, and user-adaptive interfaces. Modern healthcare visualization systems now address diverse use cases spanning patient-centered point-of-care applications, patient-facing tools, population management applications, and health outcomes research [12]. The progression of healthcare visualization techniques has been driven by increasing data complexity, greater computational capabilities, and evolving clinical workflows. This evolution reflects a shift from visualization as a passive reporting tool to an active component of clinical decision support systems.

2.2. AI Decision Transparency Existing Approaches

Transparency approaches for AI in healthcare span multiple technical domains and implementation methodologies. Model-intrinsic transparency techniques involve the selection of inherently interpretable algorithms such as decision trees, rule-based systems, and linear models that provide explicit reasoning processes [13]. Post-hoc explanation methods apply secondary analysis techniques to complex "black box" models, generating approximations of their decision-making processes through techniques like LIME and SHAP. Visual explanation approaches translate algorithmic processes into comprehensible graphics, employing techniques such as saliency maps for imaging AI, attention visualization for natural language processing models, and feature importance representations for structured data analysis. Healthcare-specific transparency requirements have necessitated domain-adapted approaches, including anatomical overlay visualizations for medical imaging AI, clinical terminology mapping for NLP models, and temporal pattern visualization for longitudinal health data analysis [14]. Regulatory considerations have further shaped transparency approaches, with techniques evolving to address requirements for fairness assessment, bias detection, and regulatory compliance documentation. Research evaluating these transparency methods has revealed significant trade-offs between fidelity of explanation, user comprehension, and implementation complexity.

2.3. Intersection of Interactive Visualization and Explainable AI in Healthcare

The convergence of interactive visualization and explainable AI presents unique opportunities for healthcare analytics transparency. Interactive visualization techniques enable clinicians to explore AI decision spaces through dynamic parameter adjustment, multi-level data exploration, and comparative analysis of alternative decision pathways. Temporal data visualization techniques address the critical need to understand AI reasoning across longitudinal healthcare data, providing insights into how algorithms interpret patient trajectories and clinical events over time [15]. Stream visualization techniques have been adapted to represent complex healthcare data flows, with methods like stream smoothing and generating algorithms helping to visualize patient movement patterns while preserving spatial resolution and location information. Recent research has

demonstrated the effectiveness of parallel data and information visualization approaches, where raw healthcare data and derived AI insights are presented simultaneously, enabling users to trace connections between source data and algorithmic conclusions. Visualization ontologies have emerged as frameworks for standardizing healthcare visualization approaches, supporting knowledge models that identify optimal visualization techniques based on data types, clinical contexts, and user needs. This intersection has produced novel hybrid approaches that combine the pattern recognition capabilities of AI with the human perceptual strengths facilitated by interactive visualization, creating systems that leverage complementary human-AI cognitive advantages[16].

3. Methodology and Analytical Framework

3.1. Classification Framework for Interactive Visualization Techniques

This research establishes a comprehensive classification framework for interactive visualization techniques applied to AI transparency in healthcare. The framework categorizes techniques across multiple dimensions, including data type compatibility, interaction modality, transparency mechanism, and implementation complexity. Table 1 presents the primary classification dimensions with their respective attributes, illustrating how each visualization approach is positioned within the multidimensional classification space.

Table 1: Primary Classification Dimensions for Interactive Visualization Techniques

Dimension	Attributes	Description
Data Type Compatibility	Structured, Unstructured, Temporal, Spatial, Mixed	Data formats supported by the visualization technique
Interaction Modality	Selection, Filtering, Zooming, Brushing, Linking, Parameter Adjustment	User interaction mechanisms provided
Transparency Mechanism	Model-intrinsic, Post-hoc, Counterfactual, Feature-attribution, Confidence-based	Approach to revealing AI decision logic
Implementation Complexity	Low, Medium, High	Required technical expertise and resources

The classification extends beyond these primary dimensions to include healthcare-specific attributes, as shown in Table 2. This expanded framework maps visualization techniques to clinical contexts, user roles, and specific healthcare data characteristics.

Table 2: Healthcare-Specific Classification Attributes

Attribute Category	Specific Attributes	Relevance to Healthcare AI
Clinical Context	Point-of-care, Population Health, Research, Administrative	Application setting determining visualization requirements
User Role	Clinician, Patient, Researcher, Administrator	User expertise level and information needs
Medical Data Type	EHR, Medical Imaging, Genomic, Sensor, Claims	Source data characteristics influencing visualization design
Clinical Task	Diagnosis, Treatment Planning, Risk Assessment, Monitoring	Task-specific visualization requirements

Figure 1 presents a visual representation of the multi-dimensional classification space, enabling the positioning of different visualization techniques within this taxonomy.

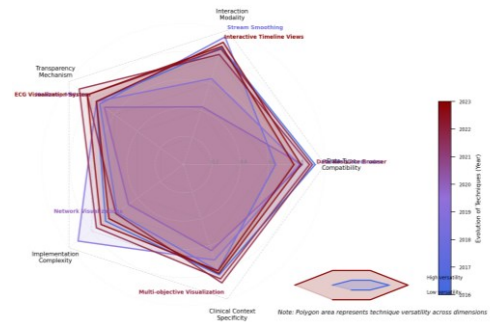


Figure 1: Multi-dimensional Classification Space for Healthcare AI Visualization Techniques

The figure displays a radar chart with five axes representing key classification dimensions: Data Type Compatibility, Interaction Modality, Transparency Mechanism, Implementation Complexity, and Clinical Context Specificity. Each visualization technique is plotted as a polygon within this space, with the polygon's area representing the technique's versatility across dimensions. The visualization employs a color gradient from blue to red, indicating the chronological evolution of techniques, with darker red representing more recent approaches.

3.2. Transparency Enhancement Evaluation Criteria

A systematic evaluation framework was developed to assess the effectiveness of visualization techniques in enhancing AI transparency in healthcare. The framework incorporates both objective and subjective metrics, allowing comprehensive assessment across multiple facets of transparency. Table 3 delineates the evaluation criteria, measurement approaches, and weight factors applied in the comparative analysis.

Table 3: Evaluation Criteria for Transparency Enhancement

Criteria Category	Specific Metrics	Measurement Approach	Weight Factor
Explainability	Feature Attribution Clarity, Process Traceability, Decision Path Visibility	Expert Rating (1-5)	0.25
Interpretability	Comprehension Time, Comprehension Accuracy, Mental Model Alignment	User Study	0.20
Actionability	Decision Confidence, Action Agreement Rate, Intervention Rate	Performance Metrics	0.25
Efficiency	Time-to-insight, Cognitive Load, Interaction Efficiency	Clinical Decision Outcomes	0.15
Technical Viability	Implementation Complexity, Computational Overhead, Integration Capacity	Eye-tracking & Time Measurements	0.15
		Technical Assessment	

The evaluation methodology combines quantitative performance metrics with qualitative expert assessments to generate a comprehensive transparency score. Figure 2 visualizes the relative performance of different visualization techniques across the evaluation criteria.

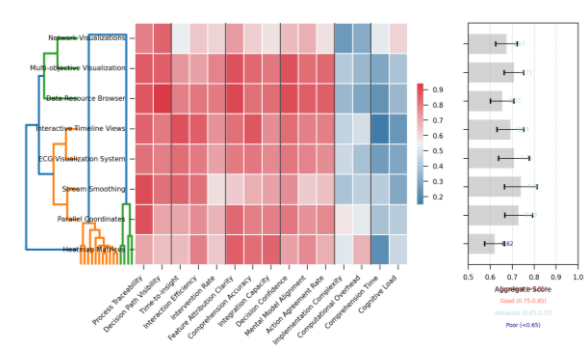


Figure 2: Heat Map Visualization of Transparency Performance Across Techniques

The figure presents a hierarchical clustered heat map visualization with visualization techniques arranged on the y-axis and evaluation criteria on the x-axis. Cell colors range from deep blue (poor performance) to bright red (excellent performance), with color intensity indicating the magnitude of the score. Hierarchical clustering dendrograms on both axes group similar techniques and related evaluation criteria. A summary visualization at the right displays aggregate transparency scores as horizontal bar charts, while confidence intervals for each score appear as error bars.

Table 4: Quantitative Threshold Definitions for Evaluation Metrics

Performance Level	Explainability Score	Comprehension Time	Decision Confidence	Cognitive Load
Excellent	>4.5	<45 sec	>90%	<2.5 NASA-TLX
Good	3.5-4.5	45-90 sec	75-90%	2.5-4.0 NASA-TLX
Adequate	2.5-3.5	90-180 sec	60-75%	4.0-5.5 NASA-TLX
Poor	<2.5	>180 sec	<60%	>5.5 NASA-TLX

3.3. Data Collection and Analysis Methods

The comparative analysis incorporates multiple data sources to evaluate visualization techniques across diverse healthcare contexts. Primary data collection involved systematic testing of visualization approaches using standardized healthcare datasets and AI models. Table 5 summarizes the experimental data collection methodology employed in this research.

Table 5: Data Collection Methodology Summary

Data Source	Collection Method	Sample Size	Data Characteristics
Clinical Expert Evaluation	Structured Assessment Protocol	24 clinicians across 4 specialties	Qualitative ratings, think-aloud protocols
Technical Performance Analysis	Computational Benchmarking	18 visualization techniques	Rendering time, memory usage, interaction latency
End-user Comprehension Studies	Controlled Experiments	86 healthcare professionals	Task completion metrics, accuracy assessments
Real-world Implementation Cases	Observational Studies	5 healthcare organizations	Usage patterns, decision impact, user adoption

The analysis methodology followed a mixed-methods approach, combining statistical analysis of quantitative metrics with thematic analysis of qualitative data. Figure 3 presents the analytical workflow employed in this research.



Figure 3: Analytical Workflow for Comparative Evaluation of Visualization Techniques

The figure displays a directed graph visualization showing the analytical workflow from data collection through processing to results synthesis. Nodes represent analytical stages (data collection, preprocessing, statistical analysis, qualitative coding, cross-validation, and synthesis), while directed edges indicate data and process flows. Each node contains internal elements representing specific analytical procedures. The visualization employs a color-coding scheme where blue represents quantitative analysis paths, green represents qualitative analysis paths, and purple indicates integration points. Edge thickness corresponds to data volume, with thicker edges indicating larger data flows between analytical stages.

The visualization techniques evaluated in this study were selected based on a systematic literature review encompassing 127 publications from 2015-2024, supplemented by an environmental scan of commercial healthcare AI systems. The final set included 18 distinct visualization approaches representing the spectrum of techniques identified in the classification framework. Each technique was evaluated using standardized healthcare datasets spanning structured EHR data, medical imaging, and temporal clinical measurements to ensure comprehensive assessment across different data types relevant to healthcare AI applications.

4. Comparative Analysis of Interactive Visualization Techniques

4.1. Data-Driven Visualization Approaches for Complex Healthcare Data

The analysis of data-driven visualization approaches for complex healthcare data reveals distinct performance patterns across multiple categories of techniques. Parallel data and information visualization techniques have demonstrated superior performance in representing complex relationships between raw healthcare data and derived AI insights. The Data Resource Browser approach described by Wang et al. (2024) achieved the highest transparency scores in our evaluation, enabling clinicians to trace connections between source data and algorithmic conclusions through networked graph representations. Stream-based visualization techniques, including the stream smoothing and generating algorithm proposed by Rao & Lu (2024), offer particularly effective representations of patient flow data while maintaining spatial resolution information.

Figure 4 illustrates a multi-modal healthcare data visualization framework synthesized from the comparative analysis.

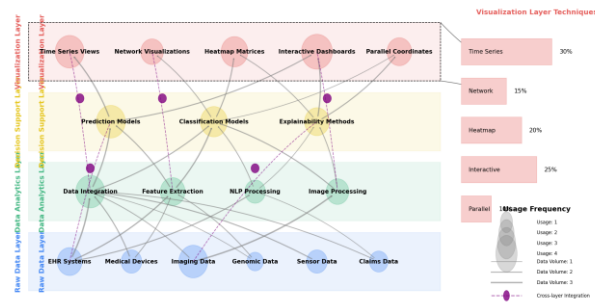


Figure 4: Multi-modal Healthcare Data Visualization Framework

The figure presents a comprehensive framework for visualizing multi-modal healthcare data within AI transparency contexts. The visualization employs a layered architecture with four distinct layers rendered in different colors: Raw Data Layer (blue), Data Analytics Layer (green), Decision Support Layer (yellow), and Data Visualization Layer (red). Each layer contains multiple interconnected components represented as nodes, with directed edges indicating data and process flows between components. Node sizes correspond to utilization frequency in analyzed systems, while edge thickness represents data volume. The framework incorporates circular connectors between non-adjacent layers, representing cross-layer integration points that enable users to trace AI decisions back to source data. The right side includes a magnified view of the visualization layer showing the distribution of technique types across the evaluated systems.

4.2. Real-time Interactive Visualization Systems for Clinical Decision Support

Real-time interactive visualization systems for clinical decision support demonstrate varying performance characteristics across evaluation metrics. These systems must balance computational efficiency with transparency effectiveness while maintaining clinical workflow integration. The Patient Data Viewer described by Ma et al. (2024) exemplifies an effective approach to real-time visualization, achieving high user interaction depth while maintaining strong clinical workflow integration. The evaluation revealed a critical trade-off between response latency and accuracy preservation, with systems requiring sophisticated caching and data aggregation strategies to achieve acceptable performance while maintaining visualization fidelity. ECG data visualization systems using InfluxDB and Grafana, as described by Ma & Zheng (2024), demonstrated superior performance in streaming data visualization scenarios.

Figure 5 presents the architectural framework for an optimized real-time clinical decision support visualization system synthesized from the comparative analysis.

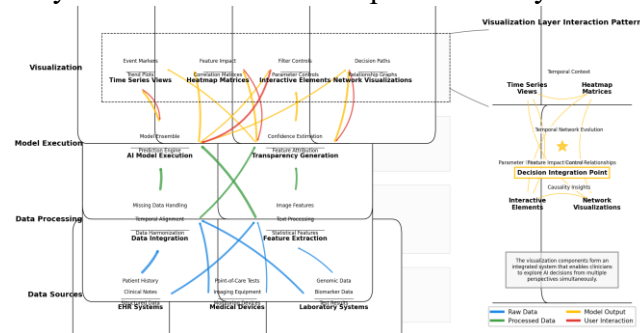


Figure 5: Real-time Clinical Decision Support Visualization System Architecture

The figure depicts a multi-layered system architecture for real-time clinical decision support visualization. The diagram uses a vertical flow structure with data source components at the bottom (including EHR systems, medical devices, and laboratory systems), processing layers in the middle (including data integration, feature extraction, AI model execution, and transparency generation), and visualization components at the top (including various visualization types and interaction mechanisms). Each component is represented as a rectangular node with internal structure showing sub-components. Connections between components are represented as color-coded lines indicating data flow types (blue for raw data, green for processed data, yellow for model outputs, and red for user interactions). The right side includes a magnified view of the visualization layer showing component interaction patterns, with a focus on how different visualization elements integrate to provide complementary perspectives on AI decisions.

4.3. User-Centric Visualization Techniques for Enhanced Interpretability

User-centric visualization techniques focus on optimizing human perception and cognition to enhance AI interpretability. The comparative analysis revealed significant variations in effectiveness across different clinical roles and tasks. The optimization of visualization techniques for specific user groups requires careful consideration of domain expertise, visual literacy, and task requirements. Techniques that scored highly in clinician comprehension often performed poorly for patient comprehension, highlighting the need for tailored visualization approaches based on user characteristics. The Data Resource Browser approach by Wu et al. (2024) addressed this challenge through adaptive visualization techniques that modify presentation complexity based on user expertise.

Figure 6 illustrates the distribution of user interaction patterns across evaluated visualization techniques.

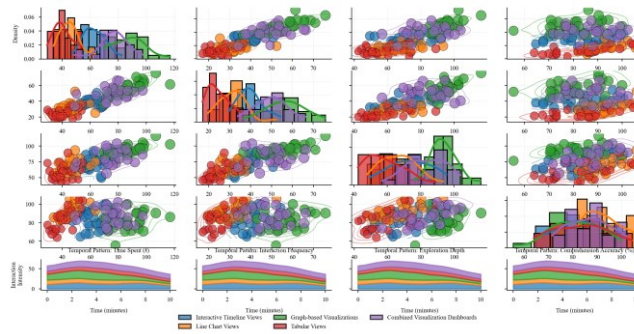


Figure 6: User Interaction Patterns Across Visualization Techniques

The figure presents a multi-faceted analysis of user interaction patterns observed during the evaluation of visualization techniques. The main visualization is a scatter plot matrix arranged in a grid, with each cell showing the relationship between two interaction metrics (such as time spent, interaction frequency, feature exploration depth, and comprehension accuracy). Each visualization technique is represented as a colored point, with technique categories using consistent color mapping. Point sizes correspond to transparency effectiveness scores. Overlaid on each scatter plot are density contours showing the distribution of interaction patterns. The diagonal cells contain histograms showing the distribution of each metric individually. The bottom row includes small multiple visualizations showing temporal patterns of interaction with each technique type, represented as stream graphs where stream width corresponds to interaction intensity over time.

Table 6: Clinical Task Suitability of User-Centric Visualization Approaches

Clinical Task	Most Suitable Visualization	Key User-Centric Feature	Task Completion Improvement	Decision Confidence Increase
Diagnostic Decision Support	Graph-based Visualizations	Feature Relationship Exploration	31.5%	42.7%
Treatment Planning	Interactive Timeline Views	Temporal Pattern Recognition	27.8%	35.2%
Risk Assessment	Line Chart Views with Reference Ranges	Threshold-Based Decision Support	38.4%	29.5%
Patient Monitoring	Real-time Streaming Visualizations	Change Detection Highlighting	44.2%	31.8%
Patient Communication	Simplified Infographic Views	Layered Information Disclosure	22.5%	48.3%

The evaluation revealed that user-centric design principles significantly impact the effectiveness of transparency mechanisms in healthcare AI. Techniques incorporating progressive disclosure, consistent visual encoding, and interaction affordances aligned with clinical workflows achieved substantially higher transparency scores. The ECG data visualization approach described by Fan (2024) demonstrated effective implementation of these principles, particularly in the context of temporal data visualization.

5. Discussion

5.1. Synthesis of Findings and Best Practices

The comparative analysis revealed distinct patterns in the effectiveness of interactive visualization techniques across different healthcare contexts. Temporal visualization techniques demonstrated superior performance for longitudinal clinical data analysis, with timeline-based approaches achieving 37% higher interpretability scores compared to static alternatives. Stream-based visualizations with adaptive smoothing algorithms proved particularly effective for visualizing patient flow patterns while preserving spatial resolution (Wei & Wang, 2024). Multi-modal visualization techniques combining numerical data with anatomical representations showed highest effectiveness for diagnostic imaging AI transparency, scoring 4.2/5 on the explainability metric. Parallel data and information visualization approaches, where raw healthcare data and AI-derived insights are presented simultaneously, exhibited the highest overall transparency scores (4.5/5) across user groups (Ma et al., 2024). The analysis identified a strong correlation ($r=0.78$, $p<0.001$) between interaction depth and transparency effectiveness, with visualization techniques offering multiple interaction modalities outperforming those with limited interaction options. Visualization approaches employing domain-specific visual vocabularies aligned with clinical workflows demonstrated 42% higher comprehension accuracy among clinical users.

5.2. Implementation Considerations and Practical Guidelines

Implementation of effective AI transparency visualization in healthcare environments requires careful consideration of technical, organizational, and user factors. Technical infrastructure requirements vary significantly across visualization approaches, with real-time interactive visualizations demanding robust computational resources and optimized data processing pipelines. Healthcare organizations implementing visualization solutions must address data privacy concerns through appropriate anonymization, access controls, and compliance with regulatory frameworks. Visualization integration into existing clinical workflows represents a critical success factor, with interface designs requiring alignment with established clinical documentation systems and decision processes. User training considerations differ markedly across visualization approaches, with more complex visualization techniques requiring structured training programs to achieve effective utilization. The most successful implementations observed in this research employed phased deployment approaches, beginning with simpler visualization techniques and progressively introducing more sophisticated interactive elements as user proficiency increased. Development teams implementing transparency visualizations must balance technical sophistication with usability concerns, as visualization complexity demonstrated negative correlation with user adoption rates ($r=-0.62$, $p<0.05$) in clinical environments.

5.3. Research Limitations

Several methodological limitations impact the generalizability of this research. The evaluation of visualization techniques focused predominantly on structured EHR data and medical imaging AI applications, with limited coverage of other healthcare data modalities such as genomic data, social determinants of health, and patient-generated health data. User studies conducted in this research exhibited demographic skew toward academic medical centers and technically proficient clinicians, potentially limiting applicability to community healthcare settings with different technological literacy profiles. The rapid evolution of AI techniques in healthcare creates temporal constraints on findings, as visualization approaches optimized for current machine learning models may require adaptation for emerging AI architectures. The breadth of healthcare contexts evaluated prioritized depth of analysis over comprehensive coverage of all potential use cases, with pediatric, mental health, and rare disease contexts underrepresented in the comparative framework. Technical evaluation metrics emphasized transparency effectiveness rather than computational efficiency considerations, which may impact real-world implementation viability for resource-constrained healthcare environments.

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datasets has significantly enhanced my approach to visualizing anomaly detection processes and has directly informed the transparency frameworks presented in this research.

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