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A Systematic Review of Human-Computer Interaction and Explainable Artificial Intelligence in Healthcare with Artificial Intelligence Techniques

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***Abstract*—Artificial Intelligence (AI) is a growing technology. Recently, AI has become popular in many fields like customer support, healthcare, and security. To make AI more user-friendly, scientists are combining it with human-computer interaction (HCI). This helps create smart systems that people can easily interact with. Human-Computer Interaction (HCI) is a field that combines AI and human-computer interaction to create intelligent systems.**

AI and HCI are used together in many fields using algorithms and providing transparency to users. This article explores the connection between AI and HCI. The goal was to find the intersection point between AI and HCI. Explainable Artificial Intelligence (XAI) is a key point that connects HCI and AI. The study reviewed literature on XAI, its areas, goals, and challenges. The study also focused on using AI, HCI, and XAI in healthcare. The study identified gaps in XAI in healthcare and its future potential. The literature shows that XAI in healthcare is a new area that needs more research in the future.

***Index Terms*—Artificial intelligence, explainable artificial intelligence, healthcare human -computer interaction, human – centered design, machine learning usability, user – centered design.**

I. INTRODUCTION

Today, digital technology is being used for communication.

Computing has become an essential part of all industries.

Mobile computing has become a major factor in today's era. [1] Technological interaction is important in many advanced areas.

Interaction factors are also important from a technical perspective.

They make it easy for people to use and manage technology. [2] Artificial Intelligence (AI) is making interactions more flexible and intelligent.

AI is doing this by integrating itself into systems using various technology acceptance theories.

This helps make interactions smarter and more adaptable. [3] Human-Computer Interaction (HCI) is a field that makes technology easy to use for people.

HCI helps create user-friendly interfaces that make it simple for people to interact with technology. [4] Artificial Intelligence (AI) makes interactions smart.

AI helps create intelligent systems that can understand and respond to human needs.

[5] A new era has connected human-computer interaction and artificial intelligence through Explainable AI.

The main goal of Explainable AI (XAI) is to explain interactions to users, creating a trustworthy environment. [6] Explainability in AI is a growing field that applies to many areas, including: Healthcare, Business, Security, Finance, Self-driving cars, Self-driving cars, AI for designers

[7] This research focuses on Explainable Artificial Intelligence (XAI) and its challenges in healthcare. The main goals are:

1. Identify issues in Human-Computer Interaction.
2. Review Machine Learning characteristics.

3. Explore XAI techniques.
4. Identify XAI challenges.
5. Review XAI in healthcare.
6. Identify healthcare challenges for XAI.

II. METHODOLOGY OF RESEARCH

This section will elaborate on the research design and set of research papers explored in the literature, with additional data sources and explanation criteria.

Research Questions:

A. What is the Significance of ML Characteristics?

Machine Learning (ML) characteristics are important because they help us understand how well a model is performing. Here are some key ML characteristics and why they matter:

1. Accuracy: How often is the model correct? High accuracy means the model is good at making predictions.
2. Precision: How often does the model correctly identify positive results? High precision means the model is good at avoiding false positives.
3. Recall: How often does the model correctly identify positive results? High recall means the model is good at detecting true positives.
4. F1-Score: A balance between precision and recall. A high F1-score means the model is good at both precision and recall.
5. Mean Squared Error (MSE): How far off are the model's predictions from the actual values? Low MSE means the model's predictions are close to the actual values.
6. Confusion Matrix: A table that shows how well the model is doing. It helps us understand how many true positives, false positives, true negatives, and false negatives the model is predicting.

B. What are the problems and challenges in XAI?

Here are the problems and challenges in XAI (Explainable Artificial Intelligence) explained in simple terms:

1. Explaining complex models: XAI models can be hard to understand, especially when they're complex and deep.
2. Model complexity: Complex models are harder to explain, and this problem gets worse when models are combined.
3. Data quality: XAI models rely on good data. If the data is bad or biased, the explanations will be too.
4. Trustworthiness of explanations: Can we trust the explanations given by XAI models? This is a big challenge.
5. Updating models: When XAI models are updated, their explanations can change too. This can be a problem.
6. Scalability of explanations: XAI models can struggle to explain large datasets.
7. Security of explanations: XAI models can reveal sensitive information if not designed carefully.
8. Lack of standards: There's no standard way to explain AI models, making it hard to compare and evaluate different models.
9. Human interpretation: XAI models rely on humans to interpret their explanations. This can lead to errors and biases.
10. Balancing transparency and complexity: XAI models need to balance being transparent and easy to understand with being complex and accurate.

These challenges highlight the need for ongoing research and development in XAI to make AI models more transparent, explainable, and trustworthy.

C.What is the future of XAI in healthcare?

Future of XAI in healthcare:

1. Widespread adoption: XAI will become a standard tool in healthcare, helping doctors and nurses make better decisions.
2. Personalized medicine: XAI will enable personalized medicine by providing insights into individual patient characteristics and treatment responses.
3. Disease diagnosis and prevention: XAI will aid in early disease diagnosis and prevention by analyzing large amounts of medical data.
4. Clinical decision support: XAI will provide real-time clinical decision support, helping doctors and nurses make informed decisions.
5. Telemedicine and remote healthcare: XAI will enable remote healthcare monitoring and diagnosis, improving access to healthcare services.

III. RESULTS

A. HCI in AI-Driven Healthcare

Human–Computer Interaction frameworks emphasize user-centered design principles to ensure that AI systems in healthcare are intuitive and accessible. Key contributions include:

- Development of interactive dashboards for visualizing patient data.
- Usability testing of AI tools among clinicians and patients.
- Designing interfaces that support decision-making under uncertainty.

B. XAI Techniques in Healthcare

Explainable AI methods aim to make complex AI models more transparent. Commonly used XAI techniques in healthcare include:

- Model-agnostic methods: SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations).
- Model-specific techniques: Attention mechanisms in neural networks, saliency maps for imaging data.
- Visualization tools: Heatmaps and feature importance graphs for clinical decision support.

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D. Integration of HCI and XAI

The integration of HCI and XAI in healthcare applications has demonstrated several benefits:

- Improved trust and acceptance of AI systems.
- Enhanced understanding of AI outputs by non-technical users.
- Better alignment of AI functionalities with clinical workflows.

E. Challenges

- Technical Complexity: Bridging the gap between highly technical XAI models and user-friendly HCI interfaces.
- Ethical Considerations: Balancing transparency with data privacy and security.
- Domain Knowledge: Incorporating clinical expertise into HCI and XAI designs.

IV. DISCUSSION

A. Current Trends

Recent studies highlight the growing importance of interdisciplinary collaboration in designing AI systems for healthcare. Examples include:

- AI-powered diagnostic tools that provide visual and textual explanations.
- Predictive models with interactive explanations tailored for clinicians.

B. Opportunities

- Personalized Healthcare: Using XAI to deliver patient-specific insights.
- Education and Training: Developing HCI frameworks to train clinicians on AI tools.
- Policy and Governance: Establishing standards for explainability and usability in AI-driven healthcare.

C. Future Directions

- Enhancing the interpretability of deep learning models through advanced XAI techniques.
- Incorporating real-time feedback from clinicians to improve HCI designs.
- Exploring the ethical dimensions of AI explainability in healthcare.

V. CONCLUSION

The integration of Artificial Intelligence (AI) in healthcare has the potential to transform the way medical professionals diagnose and treat patients. However, the lack of transparency and explainability in AI decision-making processes raises concerns about trust, accountability, and patient safety. This systematic review aimed to investigate the current state of Human-Computer Interaction (HCI) and Explainable Artificial Intelligence (XAI) in healthcare, with a focus on AI techniques'

In conclusion, this systematic review highlights the importance of HCI and XAI in healthcare, and provides a roadmap for future research in this area. The integration of HCI design principles and XAI techniques can improve the transparency, explainability, and trustworthiness of AI-based healthcare systems.

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