An Analysis of the Impact of Human-Computer Interaction on Artificial Intelligence in Healthcare

Vaghani Divyeshkumar
divyeshvaghani96@gmail.com
Gannon University, 109 University Square,
Erie, PA 16541, USA

Abstract

Human-computer systems (HCIs) interaction inspects how people develop, implement and utilize interactive computer systems and how computers affect people, organizations and society. Human-Computer Interaction (HCI) is a field that has been combining Artificial Intelligence and human-computer engagement over the past several years in order to create an interactive brilliant system for user interaction. This consists of not only ease of use but also new interaction tools that encourage user practices, enable access to data and make communication more effective. Knowledge is given and requested, how computer operations are handled and monitored and recorded, all forms of help, documentation and training, the techniques used to design, build, test and ascertain user interfaces and the process developers take when designing interfaces. Artificial intelligence (AI) is one of the emerging tools. In recent decades, artificial intelligence (AI) has gained widespread acceptance in a variety of fields, including virtual support, healthcare, and security. AI, in conjunction with HCI, is being used in a variety of fields by employing different algorithms and employing HCI to provide transparency to the user, allowing them to trust the machine. The inclusive examination of both the areas of AI and HCI, as well as their subfields, has been explored in this work. The main goal of this article was to discover a point of intersection between the two fields. The understanding of Artificial Intelligence (AI), which is a linking point of HCI and AI, was gained through a literature review conducted in this research. The literature covered themes identified in the study (such as AI and its areas, major AI aims, and AI challenges). The study's other major focus was on the use of AI and HCI. The poll also addressed the shortcomings in AI in healthcare, as well as the field's future potential. As a result, the literature indicates that AI is still a novel subject that has to be explored more in the future.

Keywords: Artificial Intelligence, Deep Learning, Explainable Artificial Intelligence, Healthcare, Human-Computer Interaction, Human-Centered Design, Machine Learning, Usability, User-Centered Design.

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I. INTRODUCTION

Nowadays, digital tools have been adopted for interaction in the modern world. Computing has become one of the most essential and integral parts of all industries and disciplines. Among all the advanced tools, mobile computing has become one of the dominant factors in today's era (Grudin, 2019). Technological interaction has been given importance in many advanced areas. Interaction factors also have significant importance in the technical perspective for being easily used and managed by the person using it (Zeng, Chen & Lew, 2020). Artificial intelligence plays a vital role in making interaction more flexible and brilliant by integrating itself within the systems with the help of different technology acceptance theories (Sohn& Kwon, 2019). Human-Computer Interaction is the field that is mainly used for making technological interaction easy for the user (Yun, Ma & Yang). Artificial intelligence, in other words is known for making interactions brilliant (Bryndin, 2020). A new era has created a bridge between human-computer interaction and artificial intelligence by introducing Explainable artificial intelligence. The main focus of XAI is mainly to explain the interaction to the end-user in order to create a trustworthy environment (Shneiderman, 2020). Explainability in AI is a field that is active in a variety of domains, including medical healthcare, business processes, security, financial and legal decisions, autonomous vehicles, smartphones, and AI for designers (Barredo, Arrieta, et al, 2020).

A. Statement of the Problem

The research has shown that HCI has further divided into two of its subfields, which consist of usability and Human-Centered Design (HCD). Usability is mainly concerned with issues related to interfaces and the only problem they can encounter is a deficiency in the interfaces. The HCD challenges that may be encountered are described by Forbrig (2016), which consists of requirements that are not clear, the design solution is not correct, and the context of use is not clear. These challenges can be neglected by taking clear requirements from the client in the beginning and involving the client in it. For the design purpose, usability should be considered so that the user level can be encountered, and for the last problem, concerning the HCD context of the system, it must be understandable to achieve satisfaction from the user.

The survey disclosed many of the challenges related to the field of AI. It is emerging in many domains and has many issues and challenges identified in the literature. The major challenges identified and discussed in the papers from the literature are security, performance, vocabulary, evaluation of explanation, generalization of AI. For the challenge of vocabulary, the expertise of the audience should be involved in the AI model to determine what explanation they expect from the AI model (Barredo, Arrieta, et al., 2020). Evaluation of explanation can be explained by Ad-hoc experiments or the KPI method or in the general case, other proxy measures can be used, such as the number of rules, nodes, or input variables considered in an explanation or explainable model for evaluation (Mars, Des &Boussard, 2019).

The research in this paper has reviewed many articles which identify the gaps in AI. The domain gaps which have been viewed in this article are related to healthcare. The paper has identified many of the challenges related to AI in the healthcare domain, which consist of System Evaluation, Organizational, Legal, socio-relational, and Communicational issues. A few papers from the literature have identified some solutions for the identified issues but, others have suggested it as a research gap that needs to be filled in the future. Regarding the advancement in the field of AI in healthcare, some gaps still exist in the literature. Gaps identified in the literature consist of the development of the AI model capable of AI methods that should be useful for the end-users and clinical expertise in the medical domain or normal users or individuals. Interface development for AI for medical domains is still a challenge. The model agnostic AI model is still an open area of research (Pawar, O'Shea, & O'Reilly, 2020). Despite AI models advancement and working in the healthcare domain, transparency remains an issue that needs to be worked on in the future for improvement in the models (Yang, Ye, & Xia, 2021). The study by Payrovnaziri et al (2020) has given importance to focusing more emphasis on studying uncommon diseases for etiologies in predictive analytics to prevent extensive and expensive workups, among other things. The researchers have given the focus on using AI to assist medical professionals to overcome their medical knowledge biases.

The research mainly concentrates on the impact of Human-Computer Interaction on Artificial Intelligence and its challenges in health care. The major goals of this research paper are:

i. To determine the uses of artificial intelligence in healthcare
ii. To ascertain the relationship between human-computer interaction and artificial intelligence
iii. To identify the problems facing artificial intelligence usage in healthcare
iv. To proffer solutions to the challenges bedeviling artificial intelligence usage in healthcare.

II.METHODOLOGY

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

A. Research Criteria

Well-known researchers from the past have performed analysis of HCI, AI, and their different aspects. The following research string was used when the literature survey was performed for this paper Human-Computer Interaction, HCI, Human-Centered Design, Usability, HCI in healthcare, Artificial Intelligence, AI, Deep Learning, Machine Learning, AI In healthcare, and Challenges of AI in healthcare.

B. Data Sources

Several different data sources were used for searching the literature. Figure 1 above shows the percentage of papers taken from each data source. The research papers that were found consist of journal papers and conference papers in Google scholar, books, Scopus, and blogs. The databases that were used in the search are mentioned in Table 1. Below.

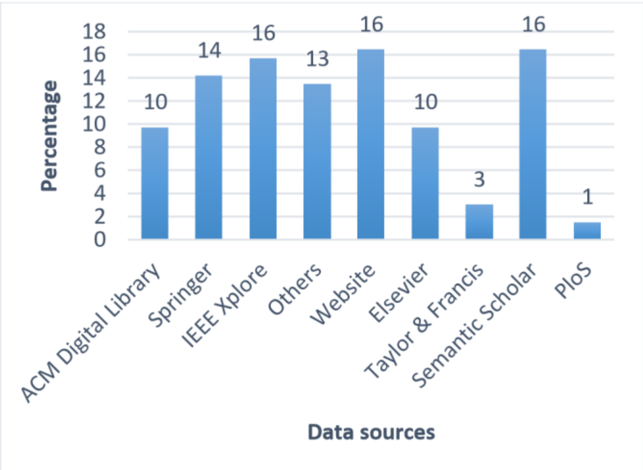


Figure 1: Percentage of Research Papers from Data Sources.

C. Exploration Criteria

Research for this paper was performed from 2016 to 2021. The paper that was evaluated first according to the criteria and keywords to be included.

Table 1: Database Engines.

Database Engines	Sources Address
ACM Digital Library	https://www.acm.org/
Elsevier	https://www.elsevier.com
IEEE Xplore	https://ieeexplore.ieee.org
Semantic Scholar	https://www.semanticscholar.org
Springer	https://www.springer.com
Taylor & Francis	https://taylorandfrancis.com

Figure 2 below shows the percentage of papers read between 2016 and 2021.

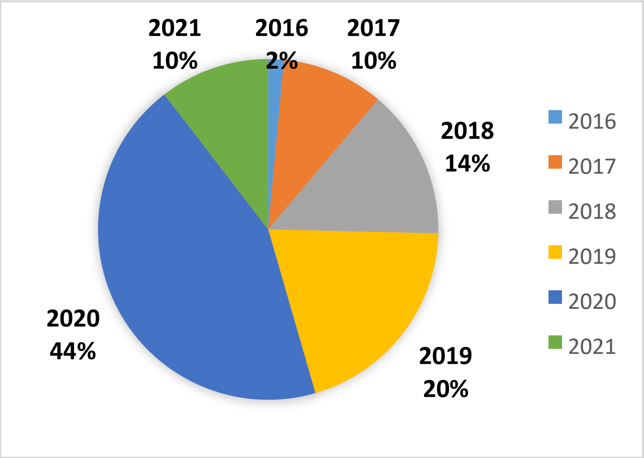


Figure 2: Percentage of Paper included between 2016 and 2021.

D. Exclusion & Inclusion Criteria

The articles that were selected consist of the HCI field and its data on subfields and the challenges that are being encountered in these fields. The key terms of HCI, Usability and Human-Centered Design were used for selecting articles in the HCI domain. For the Field of Artificial Intelligence key terms of AI, Deep Learning, and ML were used for defining the introductory part of this field.

III. RESULTS

In this section, HCI and Artificial Intelligence will be explored in terms of the fields in which they are working. This section will first give the basic understanding of HCI, and after that, AI and its related fields will be discussed in this section.

A. Human Computer Interaction

Human-Computer Interaction (HCI) is one of the fields that is emerged and has been successful in both the fields of computer science, and psychology & cognitive sciences (Kamal, Alam, Khawar, &Mazliham, 2019). HCI is also contributing to other fields of ergonomics, sociology, graphic design, and business. HCI helps human beings to understand and interact with and through technology by providing a good means of communication (Gurcan, Cagiltay&Cagiltay, 2021). The main aim supported by HCI is to provide interaction following the needs and capabilities of users (Kurilovas&Kubilinakiene, 2020). The easy structure of communication is mainly supported by technology. Psychology's role in HCI consists of a general framework for the interaction of human beings with systems and software, and it consists of verifying the usability of the system and software after it is developed (Sagar&Saha, 2020)

Challenges that are covered by HCI consist of better describing design and development work for understanding. The other thing is to better describe the role that psychology, in particular, social and behavioral science broadly plays in HCI (Hong, Hullman, &Bertini, 2020).

Human-Centered Design (HCD)

Human-centered design (HCD) is a field of HCI in which methods have been developed to understand people, culture, and co-evolution of these factors in technology. It is a field that concentrates on the development of an interactive system on making the system usable. In other words, we can define HCD as a process in which systems understand the perspective of how people think to design an effective system (Boy, 2017).

The term Human-Centered Design (HCD) is named or grown as user-centered design (UCD) due to the intersection of psychology and artificial intelligence. HCD, also known as Design Thinking (DT), and UCD can be classified as the same thing (Bezzano, Martin, Hicks, Faughnan, & Murphy, 2017).

Human-Centered Design or HCD is divided into four phases. In the first phase, stakeholders for the system or product that is being developed are identified with the help of the context of use. In the second phase, after the analysis has been done, the functional & non-functional requirements are assembled, which can also consist of domain-specific requirements. Design solutions or interfaces are collected in the third step of HCD. When the design solutions are finalized, those design solutions are evaluated in the last phase. (Ferooqui, Rana &Jafari, 2019). When we talk about the HCD phases, certain challenges may occur and require certain steps to be performed. The possible continuation consists of an analysis of context to be done for a second time if serious challenges are occurring or tend to occur. If the analysis step has been done correctly but the requirements do not seem to be according to the domain or not specified according to functional & non-functional requirements, the step needs to be performed again. The third possibility that may occur is improving the design solutions (Forbrig, 2016).

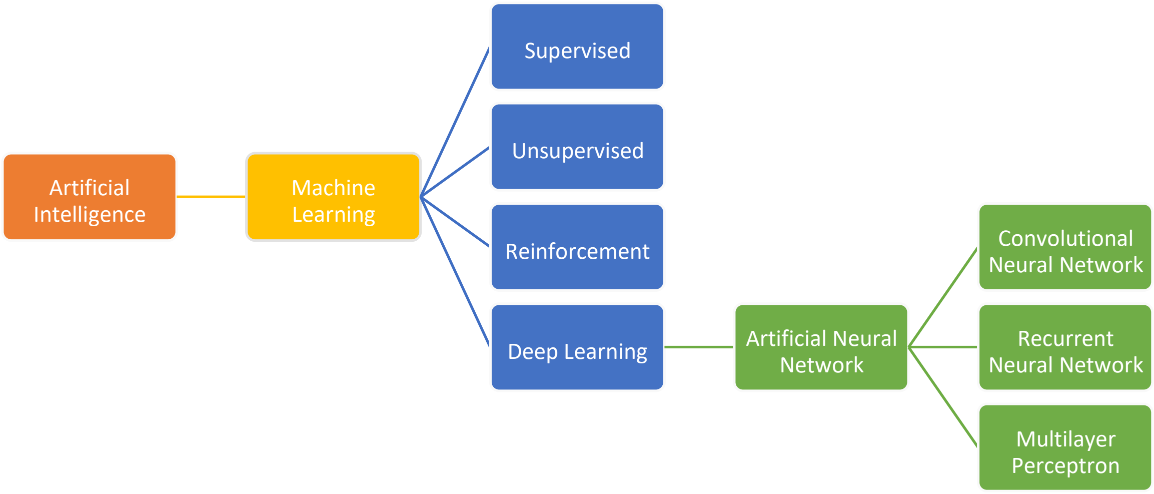
When we talk about usability and human-centered design, both fields are subfields of HCI and have many similarities. The focus of both of the fields is to provide ease to the user. The difference between the fields is that usability is performed on interfaces to check whether the particular interface is efficient and effective to achieve the satisfaction level of the user (Raduntz, Mulhausen, Furstenau, Cheladze&Meffert, 2019). On the other hand when we talk about Human-Centered Design, its main focus is to go through some of the steps to achieve the design that will be made according to the user's needs or expectations (da Silva & Marques, 2020).

B. Artificial Intelligence

The main concept or idea behind Artificial Intelligence (AI) is to understand brilliant entities. Many definitions address AI in different terminologies and frameworks. In 1990, Kurzweil defined AI as “the art of creating machines that perform functions that require intelligence when performed by people”. The other idea of AI was proposed by Winston in 1992, who defined AI as “the Study of the compilations that make it possible to perceive motive and act”. In 1993, Luger defined AI as “The branch of computer science that is concerned with the automation of brilliant behavior” (Dosilovic, Brcic&Hlupic, 2018).

Artificial Intelligence means the study of brilliant agents, which means a device that perceives its environment and takes action, which is the motive for maximizing its success in the goal. In other words, we can say that AI works as a brilliant agent that takes the best possible action in a situation (Ongsulee, 2018). AI is working in many fields, like network load balancing, smart agriculture strategies, security, livestock, inventory management, and manufacturing and production (Shahid, Islam, Alam, Su’ud& Musa, 2020; Shahid, Islam, Alam, Mazliam& Musa, 2021; Hassan, Alam, Illahi, Ghamdi, Almotiri&Su’ud, 2021). Figure 3 briefly summarizes artificial intelligence its subfields, and their further division into other subfields.

Some of the fields related to AI are discussed below:



Machine Learning

Machine Learning (ML) is the subfield of AI that discovers and constructs algorithms that can learn from and make predictions on data. It is also said that ML gives the computer the ability to learn without being explicitly programmed. ML is used in those areas where designing and programming explicit algorithms with good performance is difficult or unfeasible. ML consists of applications like email filtering and the detection of network intruders. ML also deals with computational statistics which concentrates on prediction making through the use of computers (Dunjko&Briegel, 2018). ML consists of the four widely used methods discussed below (Anandakumar&Ramu, 2020):

Supervised

Supervised learning algorithms are used where the desired output is known and is trained using labelled data.

Unsupervised

In unsupervised learning, no historical labels are used and the algorithm has to figure out what is being shown.

Semi-Supervised

Semi-supervised algorithms are used for the same applications as supervised learning. It consists of both labelled and unlabeled data for training.

Reinforcement Learning

The reinforcement learning algorithm works on the mechanism of the best policy. This algorithm consists of three primary components the agent, the environment, and actions. The objective is for the agent to choose actions that make the most of the expected reward over a given amount of time.

The agent will reach the goal much faster by following a good policy.

Deep Learning

Deep learning is a field of ML, known as deep machine learning, deep structured learning, and hierarchical learning. In deep learning, features are extracted by deep learning itself without human intervention. This technique is inspired by the structure of the human brain known as an artificial neural network (Kim, 2019).

Artificial Neural Network (ANN) - solves the challenges that would prove impossible or difficult by human or statistical standards. ANN can be said to as a piece of computing system design intended to simulate the way the human brain analyzes and processes data. ANN is further divided into three classes known as Multilayer Perceptrons (MLPs), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) (Ongsulee, 2018).

Multilayer Perceptrons (MLPs) – They are used to distort the input space to make the classes of data linearly separable. They are known as feed-forward neural networks, with a small set of requirements for data set consisting of three layers of the dataset with inner, hidden, and outer layers (Jing, Bian, Hu, Wang, Xie, 2018).

Convolutional Neural Networks (CNNs) or ConvNet – Are designed in the form of multiple arrays. An example can be taken as a simple image containing three 2D arrays. CNN's has many applications in the fields of image, video processing, natural language processing, and recommender systems (Ongsulee, 2018; Jing, Bian, Hu, Wang, Xie, 2018).

Recurrent Neural Networks (RNNs) – Tasks that involve sequential inputs in the form of speech or language, in such cases, recurrent neural networks are best used. It is used in applications for speech recognition, machine translation, and language modeling (Jing, Bian, Hu, Wang, Xie, 2018; Arras, Montavon, Muller &Samek, 2017).

IV. RESULTS

A. Human-Computer Interaction (HCI) and Artificial Intelligence (AI)

HCI and AI work hand in hand in such a way that AI mimics human beings to build brilliant systems, and HCI attempts to understand human beings to adapt the machine to improve safety, efficiency, and user experience. AI concentrates on the internal mechanism of brilliant systems and HCI concentrates on the fundamental phenomenon of interaction among people and tools. AI fieldwork to create brilliant interfaces that provide the capability to perceive, act and learn by themselves. On the other hand, HCI is focused on usability, creativity, and innovation of the system. This section addresses some of the papers that have focused on the fields of HCI and AI together as both of the fields overlap each other in different domains and the tools that are developed using both of these.

Yang, Banovic& Zimmerman (2018) provides the gap identified between HCI and ML. The Gap mainly concentrates on how to improve the design in ML for user experience (UX) Using HCI. 2494 research publications related to HCI were analyzed for this, and 3 under-explored areas were identified through this paper that can help to prepare for design innovation. The main thing that was identified during the research was that UX and ML are not addressed together. 9 papers have mentioned machine learning, 3 papers have described or given importance to the design in ML system. Two of the groups were created in this research in which the first group identified the well-established ML topics. The second group identified the under-explored ML topics. The study, after analysis, provided seven clusters of HCI concerning ML: i) brilliant UI and usability; ii) brilliant environment; iii) recommenders and user modeling; iv) social network and sensor framework; v) AI and knowledge systems; vi) search and deep learning) and vii) sentiment analysis and affective computing. The analysis identified two clusters of ML technical advances that have not yet been destined to particular conveniences, interactions, or user experiences. The first is sentiment analysis, the second is social network mining.

Wetzel, et al (2018), an AI-infused orchestration system named Formative Assessment Computing Tools (FACT) was developed for teacher management of classroom workflow that mixes small groups, individual, and whole class activities. FACT technology can provide a user experience for students that they can use on a desktop, laptop, or tablet with the help of a web browser. Students are also provided with the right to edit, draw, type, erase, or move the activities they are performing, similar to other online collaborative editors like Google Docs. The usability of the system is also being evaluated in the testing method by working on two of the factors, including time consumed in FACT and the amount of time wasted in the paper, what are the failures that are occurring in FACT and how frequently do they happen? Management on the teacher's side can be done with the help of a tablet. AI intelligence is involved in FACT in such a way that it monitors the students and edits and updates teacher dashboards in real-time to show progress and alerts.

Another paper published by Kolski, et al (2020) addresses the association of HCI and AI in different systems. The paper proposes that a brilliant system cannot perform its functions properly without a concept and design based on solid HCI principles. This paper reviews the following domains: brilliant user interfaces, and more specifically, conversational animated effective agents; capitalization, formulation, and use of HCI ergonomic knowledge for the design and evaluation of interactive systems; and synergy between visualization and data mining.

Liu, Wang, Bian, Ren & Xuan (2018), based on a proposed psychological model in the past and improvement in the brilliant system, a brilliant interactive computing model based on the human-computer cooperation mental model is proposed. For designing the proposed model, the first module was natural interaction behavior characteristics, as the design principles are used for the interface module. The second module consists of the perceptual module, which was based on the human-computer cooperation mental model and consists of sensations, attention, and perceptions. It provides the acquisition of multi-modal interactive data and, based on this, the user task intention is extracted and forwarded to the cognitive computing module to solve the task, which was the third module of this model. The cognitive computing module receives the task and solves the interaction task. Task solving is dependent on knowledge experience that is based on ML models for self-learning and knowledge updates. The results are obtained and handed over to the action response evaluation module, which is the fourth and last module of the proposed model. It provides feedback of the task processing results to the user in a natural and suitable form of representation.

Fan, Fan, Tian & Dai (2019) proposes that AI and HCI are supposed to be the era of brilliant data. Many commercial applications have a brilliant user interface that is presented in this paper. HCI and AI as the core fields consist of applications like natural gesture interaction, emotional computing, and voice dialogue systems. The human-machine dialogue-based tools that are also named in this paper including Apple Siri, Microsoft xiaoic, Google home, and amazon are solving human-machine dialogue. The paper also consists of a part that concentrates on some of the research publications done in the past that focused on combining research in HCI and AI and their future scope. This paper summarizes the ways in which we anticipate that AI and HCI research will continue and even increase, and is a useful area of research.

Tian, Fan, Dai, Du & Liu (2018) explains the history of HCI and some of the core issues addressed through the use of HCI in the interface. New thinking or ideas regarding HCI are given by describing that HCI is not said to belong only to the perspective of interface or GUI but also to its transit to the natural user interface. The interface should be more humanized that will be easy and comfortable from the user's point of view. It is also discussed from a research perspective that increased use of HCI in commercial products is also increasing for use with AI as discussed in some names in (Fan, Fan, Tian, & Dai, 2019).

Topak&Pekericli (2020) also provides the knowledge and use of HCI with AI tools. The purpose that was covered in this paper is to provide an understanding and assessment of how HCI knowledge can be used in studying new interaction modalities in brilliant built environments to make advancements in the AI field. In this direction, it is intended to review the applicable research methodologies that can be derived from the HCI research community to envision the gradual change in human experiences with and within buildings alongside the advancements in data, communication, sensor, and actuation tools.

DARPA's Explainable AI system proposed by Gunning & Aha (2019) is a program that endeavors to create AI systems whose learned models and decisions can be understood and appropriately understood by end-users. The main idea behind AI technology is to provide a variety of new ML techniques. With the advancement in modified DL techniques that learn explainable features; methods that learn more structured, interpretable, and causal models. Results indicate that these three broad strategies merit further investigation and will provide future developers with design options covering the performance versus explain-ability trade space.

B. Human Computer Interaction in Healthcare

The growing demand for healthcare technology is increasing day by day. There are many challenges and gaps that need to be closed between industry and academia to improve acceptance of technology, ensure compliance, good ergonomics, and high-performance design for all users and contexts of use. Many applications have been named for improving HCI in different research in the past regarding healthcare. Some of them consist of a natural user interface, child computer interaction, and interpretation for people with disabilities, and human factors for healthcare Ponss&Dussch (2018). This section is regarding some of the other research that has been done in the past to talk about HCI and healthcare.

Clarke, Oluwaseun& Rhoda (2017) said it gives human-robot interaction details in general. Human-robot interaction is the leading field when we talk about AI & HCI. In the past, robots have been used for industrial purposes. But nowadays, robots are also being used for social purposes. The important purpose that social robots fulfil is to fit into the human environment and socializing with humans. Healthcare sector robots are being deployed to overcome the shortage of healthcare professionals, rising costs in healthcare, and growth in vulnerable populations like the sick, aged, and children with disabilities. The challenges faced in robots are safety, usefulness, acceptability, and appropriateness. At the interaction end, the usability issues consist of privacy, trust, safety, users' attitude, culture, robot morphology, as well as emotions and deception.

Interaction (2020) has also discussed social robots as a new viewpoint in the healthcare sector. The paper discussed different robots developed in the past. Some of them consist of Nao Robot (2006), which mimics human behavior like a toy, Paro (2009), developed for supporting therapy and care of elderly patients in hospitals, Robear (2015) provide support for lifting a patient out of bed and the most popular, Sophia (2017), which learns and adapts to human behavior. The main theme behind this paper was to make it look like social robots have gained popularity in the healthcare sector and can somehow fulfil the requirements of the sector. The article presented in (Stowers&Mouloua, 2018) has presents a review of papers from 2010-2017 in which the most popular topics of HCI in healthcare are presented, including data and patient records. Some of the main important topics that were covered in the reviewed articles related to HCI consist of usability, security/privacy/trust, automation, training & simulation, data/ patient records, human factor/machine interaction, and safety. These are some of the factors that need to be covered when implementing applications relating to the medical healthcare system.

The literature review (Wiser, Durst &Wickramasinghe, 2018) presented here discussed five of the HCI theories that are considered to be the most suitable for use in the healthcare context. Theories are selected based on their popularity and consist of activity theory, actor-network theory, distributed cognition, structuration theory, and situated action. The results of the study show that activity theory is less popular than structuration theory, but with regard to HCI, it is by far the most applied theory in research. Actor-network theory and situated action are the least popular theories. Distributed cognition is not as regularly applied as activity theory, but still has a motive for its existence, as several case studies have shown. The results declared that activity theory is considered to be a valuable theory for facilitating a better understanding of tools in a healthcare context. Some of the contradiction layers that have been proposed in the paper will help to reveal key issues that, when resolved, can lead to smoother system implementation and more streamlined processes.

The literature review conducted by Sogaard& Wilson (2019) shows that many health professionals are creating internet-based treatments for mental health conditions like depression and anxiety. The main motive for conducting this literature review is to find out how sufficiently the rules of HCI and user-centered design are being incorporated. Some of the negligence that is still made in developing those applications consists of poor understanding of safety, effectiveness, dependable, credible, reliable, and trustworthy implementation of the interventions. The endorsement arising from this review is that HCI should be carefully considered when mental health nurses and other practitioners adopt e-mental health interventions for therapeutic purposes to assure the quality and safety of e-mental health interventions on offer to patients.

The systematic literature review by Ahmad &Mozelius (2019) pointed out the main concern about the need for medical care, which has been increasing for adults around the globe. The main theme behind this is successful active aging and e-health. The key research question behind the study conducted was to identify the factors for improved HCI in technology-enhanced healthcare systems for older adults. The findings of the studies show several factors needed to be considered for improvement, which consist of trust, personal integrity, technological acceptance, e-health literacy, and accessibility of Data and Communication Technology (ICT) as the most determinant. The following challenges need to be addressed and improved to make independent living easier for older people.

The literature review by Kaysi &Kesler (2018) pointed out the cross functioning of HCI and visualization tools in detail. The main theme of the review was to check how we use the HCI and visualization tool to get the users desired data from a large amount of data. Healthcare services have crucial and high-dimensional data that needed to be analyzed and integrated. The effective analysis and management of large amount of data in healthcare has become a priority. To overcome the integration problem, a new approach has been utilized in the study for effective analysis. Based on the sample research, the study focused on the capabilities and opportunities of working together with these two fields on healthcare services to get accurate and effective results. The researchers investigated and used the most popular D3.js, Welkin, and Gephi visualization tools in this study for their research.

The narrative review conducted by Melder, Robinson, McLoughlin, Iedema&Teeda (2020) provides a review of the previous studies conducted in the field of HCI in healthcare and how HCI can help improve clinicians' engagement and leadership. The literature also addresses the issue of not providing necessary data focused on frontline practice. The issues are addressed in the literature for the improvement in the complex health system to assist clinicians. The review integrated the field of HCI into the health system by highlighting the key role of clinicians. The review also proposed a clinicians and manager's guide for the planning, enacting, sustaining, and scaling of HCI. Blandford (2019) has discussed a variety of digital health tools for professional patients and analysts that support health management and discovery. The review also highlighted the benefits of digital health tools. The survey also provided ways of improving healthcare by providing an integrated development cycle in which step-by-step work will help create a good healthcare technology.

C. Artificial Intelligence in Healthcare

AI is the field that is providing opportunities for reduce costs, and influence population health (Matheny, Whicher&Thadaney, 2020), the advancement in many fields. AI is said to be applied in different types of healthcare data, which may consist of structured and unstructured data. Popular AI techniques of consist of machine learning, vector machines for structured data, and natural language processing for unstructured data. The most common disease areas in which AI is working are the fields of neurology, cancer, and cardiology (Jiang et al, 2017). It is said in many articles that AI will add capabilities that will lead to more efficient and effective care by healthcare providers (Noorbakah-Sabet, Zand, Zhang, &Abedi, 2019). AI in healthcare is said to be the hope, the hype, and the promise (Matheny, Whicher&Thadaney, 2020). In this section, some of the papers from the literature have been reviewed from the AI perspective in healthcare, the challenges, and what could be the future of AI in healthcare.

A paper published by Jiang et al (2017) reviewed the importance of AI in healthcare and provided a literature survey of the applications of AI in healthcare in three major areas of early detection, diagnosis, and treatment as well as outcome prediction and prognosis evaluation. The motivation of AI systems is to reduce diagnostic and therapeutic errors that are unable to be overcome in normal human clinical practice.

The paper provided the analysis of ten diseases in which the AI working fields consist of neoplasms, nervous, cardiovascular, urogenital, pregnancy, digestive, respiratory, skin, endocrine, and nutritional diseases. The most common areas among these diseases consist of cancer, neurology, and cardiology due to the severity of these diseases. This is the motive that early diagnosis is an important factor in these fields. The review provided the importance of AI based on the fact that AI will unlock massive hidden data from the field of healthcare that will assist physicians in making better clinical decisions in the near future. The paper provided machine learning algorithms in the medical literature which are used for searching the data within healthcare. The most common algorithms that have been used in ML consist of Support Vector Machine (SVM) and Neural Network (NN). Input to the ML algorithm consists of patient traits and some medical outcomes. Some of the baseline traits of patients consist of age, gender, and disease history, and disease-based data such as diagnostic imaging, gene expression, EP tests, physical examination results, clinical symptoms, and medication. Patient medical outcomes that may be needed for ML inputs consist of indicators, patient survival time, and quantitative disease levels.

Another paper published by Noorbakah-Sabet, Zand, Zhang, &Abedi (2019) is a review of ML in healthcare, traditional, clinical, and public health applications with an important role in privacy, data sharing, and genetic data. This paper concentrates on the implementation of AI in the healthcare fields in disease diagnosis & prognosis, treatment optimization and outcome prediction, drug development, and public health. In ML, AI is used for making automated clinical decision systems. The main concern with technological advances is that they require collecting and sharing a massive amount of data, which will generate privacy concerns. The paper points selected areas in which ML has high potential in clinical translation and public health, which consist of clinical disease prediction and diagnosis, drug discovery and repurposing, and public health (epidemic outbreak prediction). The study pointed out that the research done in the past has focused on cancer, the nervous system, and cardiovascular disease. Studies show that many of the drug discoveries done in the past are the motive for combining different domains accidentally. ML is used in drug discovery for making crossdomain linkage due to the high cost of drug development. In public health epidemic outbreaks predictions such as peak and duration of infection can be easily made possible if model parameters are partially known, as done by Kanza& Frey (2019). Some of the challenges regarding healthcare that have been identified in this study consist of privacy, interoperability, and the issue of trust.

The paper published by Mahajan, Vaidya, Gupta, Rane& Gupta (2019) reviews the status of AI in developing nations like India and highlights some of the factors that can be beneficial for providing new directions and opportunities for AI in healthcare. The field that is pointed out in this review is the field of Radiology. Radiology is said to be one of the most evolving fields of medicine. AI-infused systems have already been developed in the past for the field of radiology, including the Missouri Automated Radiology System (MARS), a computer-based expert system being developed for radiologists (ICON), Pheonix, and MARS II. The ethical framework for AI in radiology consists of autonomy, beneficence, justice, explicability, and transparency. The study proposed that AI and radiology can be combinable in the form of Augmented Intelligence, which will make the future of healthcare lively. Reviews for AI in healthcare are also presented in one of the papers by Yang, Ye & Xia (2021), which surveys the present state of healthcare applications and the projects related to them. The medical literature shows that sophisticated algorithms can be developed using AI to read features from vast datasets of healthcare data and can use the knowledge learned to help clinical practice. The review shows that AI systems can help reduce medical & therapeutic mistakes. The Clinical Decision Support System (CDSS) in medicine was famous in the mid-twentieth century. Rule-based models in the field of healthcare are found to be unstable and can require clear expressions of decision rules. Hence, the paper proposes that with the involvement of AI in healthcare, patients' satisfaction needs to be maximized.

Fritchman, et al (2018) presents the first secure multiparty computation (SMC) enabled cryptographic protocols for private classification with tree ensembles, random forest, and boosted decision trees. The SMC system was also integrated with the KenSci healthcare analytics problem and is also supposed to be one of the first privacy-preserving machine learning protocols implemented in a real-world scenario. The review also shows that there are still gaps in security protocols to be implemented in healthcare and can be worked on for future research.

D. Challenges of AI in Healthcare

The advancement of AI is integrating different AI tools. It consists of business processes, security, and AI for designers. Healthcare is one of the fields which is now improving itself by integrating technological advances in it. In the past, different ML algorithms were used in the healthcare domain for the diagnosis of diseases and new drug production for patients. AI is one of the factors which is now being used along with healthcare for making the healthcare sector more advanced. Research by Payrovnaziri et al (2020) has been conducted for the review of existing AI systems which are using electronic health records and for providing the techniques that have been used in these studies along with the research gaps and challenges to cater to future perspectives. The study shows that further research needs to be done in AI for the medical field, along with the review that such research will be helpful for medical professionals, and many opportunities exist for working in this domain.

Another research conducted by Pawar, O'Shea, Rea, &O'Reilley (2020) expressed concern about the difficulties of restricting the AI model to specific domains in order to achieve greater accuracy. Another issue raised in the paper was the need to explain AI techniques so that they are easily understood by model users and the medical healthcare system. Lastly, the issue of the development of appropriate user interfaces was suggested for effectively displaying data related to AI.

Payrovnaziri et al (2020) have provided different challenges related to AI concerning healthcare. The first issue was that visualization does not always provide good explainability to health professionals. The robustness of the system should be increased by adding more features related to AI. More features added to the AI will help to increase the accuracy of the AI model. The other challenge was that the predictive analysis provided by the model will raise false causation which may not be true related to the said disease and insufficient explainability is one of the causes of not adapting AI in healthcare.

Yang, Ye & Xia (2021) has focused on the challenge of explainability and transparency of the AI model, which may cause inadaptability of AI models in the healthcare sector. Another study by Pawar, O'Shea, Rea, O'Reilly (2020) raised the concern of a lack of explainability and operations of AI in clinical expertise, which could be a problem for adaptability. The other main issue is integrating AI with existing ML workflows and the lack of high-level explainability related to ML models.

E. Our Contribution

The paper provides an overview of HCI, and AI based on the literature, which would be beneficial to anybody interested in these topics. Because all of these disciplines have fundamental data in the literature. The characteristics of ML were also examined in many domains. In the realm of AI, ML characteristics are extremely important to incorporate into different models. The field of Explainable Artificial Intelligence, as well as its techniques, was another focus of the review. The relevance of different AI explanation approaches in different domains has been established through a review in which visual explainability is used to describe visual explanation of model behavior. The text explanation approach is another strategy that is used to provide text for describing the model. The healthcare area was the primary focus of this AI evaluation. The review also discussed the relevance of AI in healthcare and previous research, as well as the challenges associated with each review. Interpretability, inadequate explainability, and model correctness are among the most significant challenges addressed in different studies.

Limitations of This Review:

For the literature review, only a small number of databases, journals, and conferences were evaluated. Before 2016, no articles were listed. The number of strings and keywords that could be used to search the literature was restricted. Finally, the study focused on the fundamentals of HCI, AI, and its developing fields of XAI in healthcare, as well as the challenges that come with them.

V. CONCLUSION

This study presents a comprehensive review of an emerging XAI area that combines Human-Computer Interaction with Artificial Intelligence. The papers chosen for the evaluation were divided into areas such as HCI, AI, XAI & Impacts, and application of these domains in healthcare. The article highlighted the relevance of the domains of HCI and AI, as well as the newly found area of Explainable Artificial Intelligence, which was created by merging the two areas. Along with the contributions and good XAI in many areas, this article also discusses the goals of XAI and the work of XAI in healthcare, as well as the challenges of XAI in the healthcare sector. Because machine learning (ML) is a popular topic in AI due to its algorithmic contributions and features, this study concentrates on ML's key properties and explainability approaches. The challenges of healthcare can be used in this study to better focus on the study's shortcomings and how to close them.

A. Future Directions

XAI is a new field that improves user trust by bringing people into the loop and eliminating transparency concerns. Future research should be conducted on the XAI algorithms in order to assess their effectiveness and make them more beneficial for application in many areas. The difficulties indicated by the review, which consist of enhancing and adding new explainability approaches linked to certain domains, as well as improving model interpretability and accuracy concerns, are another area that should be given priority in the future.

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