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1. Information visualisation and health

At the core of multiple discussions on visualisation (M. Chen et al., 2014; Engelbrecht et al., 2015; Kochhar et al., 1991) lies the concept that a visualisation solution should culminate in meaningful insights. Even when the emphasis of a visualisation task is on gaining insights, it remains challenging to ascertain the nature, extent, or accuracy of the acquired insights (M. Chen et al., 2014). Despite there being many interpretations of visualisation, Chen et al. (2014) provide the most complete description:

"Visualisation (or more precisely, computer-supported data visualisation) is a study of transformation from data to visual representations to facilitate effective and efficient cognitive processes in performing tasks involving data. The fundamental measure for effectiveness is correctness and that for efficiency is the time required for accomplishing a task." (M. Chen et al., 2014)

The field of Information Visualisation focuses on designing and developing representations that resonate with viewers' mental models, facilitating comprehension of data and fostering new insights (Spence, 2001), enabling analytical reasoning within constrained timeframes, providing viewers with enhanced capacities to assess, strategies, and make decisions, allowing individuals to grasp vast amounts of information concurrently while succinctly summarising analytical outcomes (Sharma et al., 2018). Information visualisation entails converting raw, lower-level data into visual representations that convey extracted meanings derived from the data (Engelbrecht et al., 2015). Therefore, information visualisation involves the graphical representation of data or information, utilising visual elements such as charts, graphs, and maps to enhance understanding (Engelbrecht et al., 2015; M. C. Kim et al., 2016; Sharma et al., 2018). Visualisation aims to convey information effectively, enabling users to discover patterns, trends, and insights within datasets (Engelbrecht et al., 2015; M. C. Kim et al., 2016). This approach capitalises on the innate ability of the human visual system to process information swiftly, surpassing the comprehension achieved through textual or numerical formats (M. C. Kim et al., 2016).

Information visualisation is a powerful tool across various domains, such as healthcare, business, science, and technology, by making intricate concepts more accessible and interpretable (Jaspersoft, 2024; M. C. Kim et al., 2016). In healthcare, information visualisation is used to represent patient data, medical images, and clinical outcomes (Kochhar et al., 1991; Ploderer et al., 2016; Sharma et al., 2018). It aids healthcare professionals in quickly grasping complex medical information, facilitating better decision-making and improving overall patient care (Engelbrecht et al., 2015).

The following sections will systematically examine the intersection of information visualisation with key components of healthcare. The aim is to analyse how information visualisation techniques contribute to understanding patient health data and bolster the effectiveness of clinical decision support tools.

1.1. Information visualisation and patient health data (self-tracking / self-care)

[to be concluded by CMU]

Interpreting health data poses a challenge, particularly as individuals become more health-conscious and take more responsibility for their well-being. Those diagnosed with specific conditions must comprehend and manage these conditions to improve their health and overall quality of life (Faisal et al., 2013). Understanding one's health conditions also enables effective communication with health professionals (Ploderer et al., 2016). In various countries, individuals are gaining more control over and access to their health records, often encouraged by healthcare services promoting principles like "no decision about me without me" (Faisal et al., 2013).

1.2. Information visualisation and clinical decision support tools

The contemporary healthcare landscape, marked by rapid decision-making (Ramalho et al., 2023), has witnessed decades of advancements enhancing the quality of life and care, resulting in increased longevity (Wilmoth et al., 2023) and a rising population of chronic patients (Ansah & Chiu, 2023). The corresponding growth in the number of healthcare professionals has not kept pace (Patlak & Levit, 2009), resulting in healthcare professionals managing elevated volumes of patients (Khairat et al., 2018).

When handling patients' data, healthcare professionals encounter diverse information, including examination results, patient-reported conditions, treatment plans, and protocols (Faisal et al., 2013). Comprehending and synthesising the extensive array of information poses a significant challenge (Faisal et al., 2013; Khairat et al., 2018). Medical studies reveal that understanding health data, particularly when in textual form (M. C. Kim et al., 2016), often necessitates additional effort to make sense of the information and apply it in practice (Ladan et al., 2018).

Incorporating Clinical Decision Support (CDS) systems into healthcare practices introduces a toolset for navigating the complexities of patient data. CDS encompasses various techniques and technologies designed to assist healthcare professionals in making informed decisions at the point of care. These systems leverage data analysis and visualisation to provide actionable insights, ultimately enhancing clinical decision-making efficiency, accuracy, and effectiveness (Khairat et al., 2018).

Information visualisation is an essential component of CDS, transforming complex medical data into understandable insights. Visualisations of CDS aid healthcare professionals in recalling similar patients' cases, exploring hypothetical scenarios, detecting inadequate treatments, tracking treatments, and supporting adherence to guidelines (Dagliati et al., 2018; Mehrdad et al., 2019). CDS utilise various information visualisation techniques to enhance the comprehension of complex medical data and facilitate informed decision-making. These techniques encompass a range of visual representations, including graphs and charts for illustrating trends, heatmaps for highlighting data intensity variations, and time series visualisations to depict temporal changes (Mehrdad et al., 2019). Treemaps represent hierarchical structures, 3D visualisations offer comprehensive views of medical data, and flowcharts map out clinical pathways (Mehrdad et al., 2019). Network visualisations depict relationships between medical entities, spatial visualisations display geographical information, and icon arrays represent data points visually (Mehrdad et al., 2019). Dashboards often integrate data from multiple sources, such as EHRs, administrative databases, and other information systems, providing a visual representation of key performance indicators in a single report (Dagliati et al., 2018; Mehrdad et al., 2019; Wilbanks & Langford, 2014). The objective of dashboards is to offer a concise overview of an array of data, resulting in several types of visualisations designed for diverse applications (Dagliati et al., 2018; Mehrdad et al., 2019; Wilbanks & Langford, 2014). The dashboards encompass a variety of represented data, including Vitals, Medication, Lab Test Results, Structured Notes, Unstructured Notes, and Personal Data (Ramalho et al., 2023).

The Electronic Health Record (EHR), a digital repository of an individual's medical information (Park et al., 2019), serves an important role in the systematic organisation and storage of comprehensive health records (ISO.org, 2023). Potential advantages of Electronic Health Records EHR include enhancing clinical decision-making, aiding in triage decisions, fostering collaboration within the care team (inclusive of patients), and boosting productivity through task automation (Rudin et al., 2020). However, EHRs are intricate and imperfect tools which can be configured, utilised, and improved in numerous, sometimes inefficient, ways (Kashfi, 2011; Rudin et al., 2020; West et al., 2015).

The integration of CDS into EHRs enhances healthcare quality compared to when these systems operate independently (Kashfi, 2011; Tcheng, 2017). CDS encompasses the use of diverse computer system tools to augment the decision-making capabilities of healthcare professionals within the clinical workflow (HealthIT.gov, 2023). CDS aim to address distinct objectives, falling into three overarching categories of use: (1) improvement of decision-making, (2) early detection of diseases and treatment, and (3) patient-centric care (Dagliati et al., 2018; Mehrdad et al., 2019; Ramalho et al., 2023). According to Mehrdad et al. (2019), the most prevalent purpose for CDS involves enhancing decision-making processes by leveraging diverse data sources to provide automated insights, evidence-based support, and wellness decision assistance (Ramalho et al., 2023). This category also encompasses monitoring individuals using intelligent systems, improving accuracy, supporting clinical workflows, and monitoring clinical pathways (Mehrdad et al., 2019).

The second category relates to early disease detection and treatment. The aim is to provide healthcare professionals with insights into specific health aspects, enabling them to make informed treatment adjustments or decisions (Ramalho et al., 2023). Here, CDS comprise systems that display real-time or evolving data used for disease monitoring, report continuous updates on specific conditions, visualise signal data for analysis, and recommend medical decisions (Mehrdad et al., 2019; Ramalho et al., 2023). The applications extend to assisting in prescribing appropriate antibiotic treatments, adopting and tracking healthier behaviours, monitoring patient safety, identifying risks for adverse events, and assessing surgery risks (Mehrdad et al., 2019).

The third category focuses on patient-centric healthcare, representing a smaller yet significant portion of CDS applications (Mehrdad et al., 2019). Here, CDS contribute to planning post-discharge care coordination and encouraging patients to actively participate in their health and treatment (Mehrdad et al., 2019), aiding clinicians in identifying potential issues during patient visits (Ramalho et al., 2023). By aligning patient values with certain normative standards, these CDSs facilitate the identification of deviations or values falling below the expected range (Ramalho et al., 2023).

1.2.1. Impact and Challenges of Information Visualisation and Clinical Decision Support

Information visualisation through CDS has seen progress, offering clinicians a transformative approach to decision-making. The customizability inherent in some visualisation dashboards allows healthcare professionals to tailor information displays, promoting individualised user experiences and enhancing overall satisfaction (Wilbanks & Langford, 2014). Moreover, CDSs contribute to decreased time spent on data gathering, reducing cognitive load and improving situation awareness, thereby streamlining clinical workflows (Faiola et al., 2015; Khairat et al., 2018).

Information visualisation is vital for healthcare professionals in data analysis and patient diagnosis. Unlike information conveyed verbally or in textual format, visually presented information can be quickly assimilated by humans (Sharma et al., 2018). The visual phenomenon is believed to trigger the recall of similar past cases into short-term memory for analytical processing (Sharma et al., 2018).

Effective information visualisation enhances cognitive processes by offering computer-supported visual representations of patient data (Faiola et al., 2015). The primary goal of visualisation is to facilitate the swift assimilation of information, recognise patterns, and derive diagnostic insights from extensive datasets (Faiola et al., 2015). Therefore, providing health professionals with suitable visualisation systems is essential to mitigate user errors and alleviate cognitive load (Faiola et al., 2015).

However, these promising strides coexist with challenges. Ploderer et al. (2016) found that visualisations which are time-consuming to analyse are overlooked despite offering more insight into a patient's health. Such visualisations are perceived as superfluous, raising concerns about the accuracy of the data without contextual patient information (Ploderer et al., 2016). Lesselroth & Pieczkiewicz (2011) point out that the heterogeneous nature of clinical data poses a significant hurdle, hindering the seamless integration of information within CDSs. The dispersed data stored across diverse systems further complicates efforts to establish a unified, comprehensive view for healthcare professionals (Lesselroth & Pieczkiewicz, 2011). Wilbanks & Langford (2014) found that sociocultural factors, such as clinician anxiety about electronic surveillance and resistance to unalterable key performance indicators, introduce complexities in effectively implementing visualisation dashboards.

Additionally, Khairat et al. (2018) and Wilbanks & Langford (2014) found usability concerns emerging prominently in the CDSs landscape. The potential for information overload and decreased acceptance among clinicians necessitates a thoughtful approach to interface design and the ability to filter out non-pertinent information (Khairat et al., 2018; Wilbanks & Langford, 2014). These unaddressed challenges may undermine the intended benefits of CDSs, impacting their integration into routine clinical practices.

1.3. Case Studies

Healthcare professionals often contend with heavy patient loads and time constraints (Khairat et al., 2018). Lack of proper understanding of clinical data could elevate the risk of misdiagnosis. Newman-Toker et al. 2022 estimate that within the 130 million annual emergency department (ED) visits in the United States, approximately 7.4 million patients (5.7%) experience misdiagnosis, 2.6 million patients (2.0%) face adverse events due to misdiagnosis, and around 370,000 patients (0.3%) endure serious harm, such as disability or death, resulting from diagnostic errors.

Zhang et al. (2013) introduced a framework applying the Five Ws concept (who, when, what, where, and why) in healthcare informatics, particularly for electronic medical record (EMR) visualisation. The study aimed to enhance the usability of information on EMRs by providing a comprehensive overview and detail-on-demand (Zhang et al., 2013). The "who" was represented as a radial sunburst visualisation of the patient's health conditions, integrated with a stylised body map indicating the "where" (Zhang et al., 2013). The "when, what, why" was depicted as a multistage flow chart covering date, symptom, data, diagnosis, treatment, and outcome (Zhang et al., 2013). The system efficiently accessed patient information, significantly reducing the time and effort for diagnostic conclusions (Zhang et al., 2013). A pilot user study with physicians and health informatics professionals revealed positive responses, emphasising the system's rapid adaptation, usefulness, and potential time-saving benefits (Zhang et al., 2013). Physicians accurately answered questions about patient history, and while preferences leaned towards sequential layouts, the radial layout's unique features, like browsing and interaction, were appreciated (Zhang et al., 2013). User feedback included suggestions for improving text readability, manual link addition, and interface interactions (Zhang et al., 2013). The study concluded by addressing limitations, such as text string length constraints, scalability concerns for large datasets, and potential extensions for richer medical information beyond standardised codes (Zhang et al., 2013).

Ploderer et al. (2016) conducted a study on developing and evaluating the "ArmSleeve" system to support occupational therapists' rehabilitation work with stroke patients. The study conducted three interconnected studies to address therapists' challenges in understanding patients' upper limb movements in daily life. Therapists were interviewed to understand their current rehabilitation practices (Ploderer et al., 2016). Subsequently, the "ArmSleeve Sensor" was designed to monitor patients' upper limb movements, followed by the creation and evaluation of the "ArmSleeve Dashboard" to visualise the collected data (Ploderer et al., 2016). The dashboard comprised four pages: overview, timeline, joint-based visualisation, and heat maps. The researchers emphasised the importance of collecting objective data for assessing exercises and activities outside therapy (Ploderer et al., 2016). The visualisations proved beneficial, offering therapists insights into patients' arm motions, educating patients, and aiding communication with other clinicians (Ploderer et al., 2016). However, the therapist expressed a need for contextual information about patients' home activities, and visualisations that were time-consuming to evaluate were disliked and often overlooked (Ploderer et al., 2016).

Rahman et al. (2016) study introduces GEAR (GamE Assisted Rehabilitation), a mobile system designed to enhance patient engagement and adherence to prescribed exercises, mainly focusing on frozen shoulder patients. The system integrated a smart wearable wristband with a sensor unit, a smartphone game application, a back-end cloud database, and a dashboard for physiotherapists. The study involved developing and evaluating GEAR Analytics, a clinician dashboard that leverages D3 (Data-Driven Documents) for data visualisation with a high level of customisation (Rahman et al., 2016). The visualisations, presented through a minimalist design, enable clinicians to analyse patient-specific exercise data, identifying trends and indicators crucial for targeted interventions (Rahman et al., 2016). The study highlighted the significance of interactive visualisations in extending clinicians' cognition and improving their ability to track gradual and sudden changes in patients' exercise patterns (Rahman et al., 2016). Clinician feedback highlighted the dashboard's effectiveness in facilitating decision-making and proposing follow-up treatments (Rahman et al., 2016). Despite positive feedback, the study acknowledges areas for improvement, suggesting incorporating more domain-specific terminology and adding a message feature for direct clinician-patient communication (Rahman et al., 2016).

Dagliati et al. (2018) focused on the development and impact assessment of a dashboard-based system within the European Union MOSAIC (Models and Simulation Techniques for Discovering Diabetes Influence Factors) project for managing type 2 diabetes. The research involved the integration of predictive modelling, longitudinal data analytics, and the reuse of data from hospitals and public health repositories (Dagliati et al., 2018). The dashboard comprised two components: one for CDS during follow-up consultations and another for outcome assessment on populations of interest (ORSS) (Dagliati et al., 2018). Visualisations included a "traffic light" metaphor for metabolic control evaluation, temporal abstractions for long-term complication episodes, and graphical displays of drug purchases (Dagliati et al., 2018). The system's positive outcome led to shorter visit durations and increased screening exams (Dagliati et al., 2018). Future adjustments may involve refining visualisations and user interface functionalities to address specific clinical questions (Dagliati et al., 2018).

Sharma et al. (2018) conducted a study addressing the complexities of clinical reasoning in healthcare settings, particularly in scenarios involving multiple morbidities, diverse patient contexts, and extensive evidence repositories. The study aimed to enhance knowledge transfer by visually presenting relevant information to patients and healthcare professionals. The study developed four diagrams for different purposes: Diagnosis Reasoning Diagram, Treatment Reasoning Diagram, Snapshot Diagram, and Pathway Diagram (Sharma et al., 2018). These diagrams aimed to support diagnostic and treatment decision-making, provide a snapshot of a patient's health status, and illustrate trajectories of health events over time (Sharma et al., 2018). The study applied Gestalt principles to assess the diagrams' coherence and gathered feedback from stakeholders, including a patient representative, a healthcare organisation quality manager, and a multidisciplinary meeting healthcare professional (Sharma et al., 2018). While participants recognised the potential benefits of specific diagrams, concerns were raised about the intuitive clarity, elements' availability from electronic health records, and the need for context in understanding the diagrams' purpose (Sharma et al., 2018).

1.3.1. Integration of Visualisation in Ophthalmology

Diseases affecting the retina, including age-related macular degeneration (AMD), diabetic retinopathy (DR), and glaucoma (GLA), are the primary contributors to blindness in individuals aged 60 years and above. Ophthalmologists often contend with the challenge of coordinating workflows involving multiple Visual Analytics (VA) tools for diagnosis (Nonnemann et al., 2021; Röhlig et al., 2023).

Nonnemann et al. (2021) and Röhlig et al., 2023 believe that there is a need for the unification of User Interfaces (UIs) to enhance the operational efficiency of ophthalmologists. Some approaches, such as applications like Dashiki (McKeon, 2009), involve integrating multiple views within a single interface through web-based mashups or webcharts (Röhlig et al., 2023). While effective, this method has limitations, with visual overload increasing as the number of integrated views grows. Alternatively, coupling views, like WinCuts (Tan et al., 2004) and Façades (Stuerzlinger et al., 2006), focus on loosely connecting independent views for interactive assembly into a common interface (Röhlig et al., 2023). This method replicates arbitrary view regions in a combined interface, emphasising task-related areas (Röhlig et al., 2023). Alternative approaches utilise visual connections between standalone views to streamline their association, either implicitly or explicitly (Röhlig et al., 2023).

Röhlig et al. (2023) addressed the challenges faced by ophthalmologists in the analysis of retinal data, where the limited integration of workflow steps, tools, and data leads to increased cognitive load. The primary goal was to reduce the overhead associated with managing tools and data during workflow execution, allowing ophthalmologists to focus on data analysis steps in cross-sectional studies (Röhlig et al., 2023). The result was a visualisation-supported tool-chaining approach to streamline the workflow, providing access to necessary tools and data while organising tool UIs on a screen (Röhlig et al., 2023). The study received positive feedback from ophthalmologists regarding the visual representation of the workflow, unified UI access to tools and data, flexibility in arranging tool views, and reduced coordination efforts in cross-sectional studies (Röhlig et al., 2023). Users appreciated summarising results directly in the UI and reducing coordination overhead in cross-sectional studies (Röhlig et al., 2023). However, there is a need to synchronise tools on the parameter level, including visualisation-specific parameters, for consistent output interpretation (Röhlig et al., 2023).

1.4. Guidelines for Integrating Information Visualisation and CDS

Engelbrecht et al. (2015) guidelines for the development of information visualisation solutions encompass practical methods to enhance data mapping to visual objects, reduction of user interactions, flexibility in approach, incorporation of supplementary information, spatial organisation, maintenance of design consistency, minimisation of cognitive load, provision of alternative information, elimination of distractions, and exploration of dataset size reduction. Sharma et al. (2018) argue that approaching visualisation design from a design theoretical perspective yields diverse visualisations compared to existing ones. Sharma et al. (2018) sought visualisations for distinct purposes, including supporting healthcare professionals in reaching diagnoses, making diagnostic reasoning explicit, aiding in treatment decisions, and enabling patient understanding. Therefore, when it comes to healthcare, visualisation can encompass diagnosis reasoning diagrams, treatment reasoning diagrams, snapshot diagrams reflecting diagnostic and treatment status at a point in time, and pathway diagrams illustrating trajectories through time of health events (Sharma et al., 2018).

Sharma et al. (2018) suggest using Gestalt principles to assess the effectiveness of designed diagrams. Gestalt psychology, encapsulating the concept of a "unified whole," involves the human capacity to combine visual elements into a logical construct through specific principles (Sharma et al., 2018). Gestalt principles include "Proximity", "Similarity", "Continuation", "Closure," "Balance", "Simplicity", "Focal Point", and "Isomorphic Correspondence" (Graham, 2008; Lester, 2003; Sharma et al., 2018; Smith-Gratto & Fisher, 1999). Achieving a state of Gestalt in the design is essential, where the foreground and background blend in a figure/ground relationship to provide a clearer picture (Sharma et al., 2018; Smith-Gratto & Fisher, 1999).

Ramalho et al. (2023) underscore the importance of aligning dashboard design with clinical workflows, adapting visualisations for comprehension, and considering single-page layouts to reduce cognitive load. Additionally, they emphasise the need to mitigate alert fatigue, implement mechanisms for data insertion, and ensure clinician training on dashboard usage (Ramalho et al., 2023). Personalisation options, iterative design based on user testing, and compatibility with various browsers and networks are also highlighted as essential considerations for effective dashboard design in healthcare settings (Ramalho et al., 2023).

Project Name (remove)	Study	Medical Field	Technology	Visualisations Used	Outcome
ArmSleeve	Ploderer et al. (2016)	Occupational Therapy (Rehabilitation)	Patient: Wearable (upper limp sensor) Health Professional: Dashboard	Dashboard: Overview page (charts and bar graphs), timeline, joint-based visualisations and heat maps. (Based on needs of OT captured during semi-structured interviews.)	Visualisations gave OT an understanding of how patients moved their arm at home. Visualisations helped to educate patients and engage with other clinicians to advocate for patients to get the required resources. OTs felt that context about the home activities was needed. Visualisations that would take too long to access were disliked and overlooked.
MOSAIC	Dagliati et al. (2018)	Diabetics	Dashboard	Dashboard: visualises drug purchases and compares patient behaviour against the population. ORSS dashboard includes charts, care-flow mining (CFM) for clinical	Clinical activities resulted in shorter visit durations and increased screening exams for complications. CDSS was deemed effective in supporting therapeutic decisions.

				pathways, and timelines for complexity care flows.	CDSS was able to identify patient subgroups and trends, facilitating efficient decision-making. The Outcome Assessment and Research Support System (ORSS) provided valuable insights for healthcare managers, enabling demographic and clinical variable analyses. The evaluation emphasised the system's efficiency in supporting clinical decisions, optimising visit duration, and enhancing diabetes management through integrated data and visual analytics.
Unified UI	Röhlig et al. (2023	Ophthalmology	Dashboard: Visualisation-supported tool-chaining approach.	Various visualisations for retinal data analysis (e.g., charts, graphs, heat maps).	User feedback was positive, citing benefits in workflow management and visualisation access.

				Unified UI visualising the workflow and coordination graph. Interviews with ophthalmologists and observations of their work were conducted to gain a comprehensive understanding of the current practices in eye analysis.	
GEAR	Rahman et al. (2016)	Occupational Therapy (Rehabilitation)	Patient: Wearable (wristband) Health Professional: Dashboard	Dashboard: Overview page showing macro, meso and micro level data (charts and bar graphs), timeline, and joint-based visualisations.	GEAR Analytics facilitated clinician decision-making, offering visualisations for patient-specific data. Clinicians suggested adding a message feature for direct patient feedback and using more specific domain terminology to enhance mapping with current practice. The minimalist design and responsiveness of the dashboard were well-received. The visualisations,

					including customisable ones implemented with D3, proved clear and effective in tracking patients' exercise progress over time.
Five Ws	Zhang et al. (2013)	Health Informatics	Dashboard: The system introduced is a framework utilising visual information displays to represent the Five Ws (who, when, what, where, why) within a healthcare informatics application. It interfaces with an Electronic Medical Record (EMR) database.	Dashboard: Radial sunburst visualisation representing the patient's health conditions. A stylised body map integrated with the radial sunburst to show anatomical locations. Multistage flow chart representing the reasoning chain (date, symptom, data, diagnosis, treatment, outcome).	The system received positive feedback from physicians and health informatics professionals. Medical coders also endorsed the system, noting significant time savings and improved coding accuracy. Physicians found the system different from what they were accustomed to but became comfortable quickly. The system's features, including the browsing highlight mode, were appreciated. Main suggestions for improvement included pre-filters for extensive data and reducing the size of the body map in the radial display.

	Sharma et al. (2018)	Health Informatics	Dashboard: Automated diagram generation from digital repositories	Diagnosis Reasoning Diagram, Treatment Reasoning Diagram, Snapshot Diagram, Pathway Diagram.	They conducted a study to enhance clinical reasoning through visual representation. Developed four diagram types for different settings, aiming to support diagnostic and treatment decisions, provide a snapshot of a patient's health status, and illustrate trajectories of health events. Applied Gestalt principles for coherence. Stakeholder feedback indicated potential benefits but highlighted concerns about clarity, element availability from electronic health records, and the need for contextual understanding. Envisions automated diagram generation for clinical use, acknowledging the need for refinement and empirical validation.

1.5. Information Visualisation and XAI

The increase in the use of artificial intelligence (AI) (Islam et al., 2022) and machine learning (ML) algorithms highlights the growing demand for transparent and comprehensible data visualisation techniques (Encarnação et al., 2022). Within this landscape, the concept of eXplainable Artificial Intelligence (XAI) has emerged, focusing on designing AI systems capable of providing clear and transparent explanations for their decisions and actions (Encarnação et al., 2022; Liao et al., 2020; Sure, 2023). The primary objective of XAI is to render the decision-making processes of AI algorithms more understandable and interpretable for humans (Shneiderman, 2020). This objective is particularly important in domains where AI decisions significantly impact individuals' lives, such as healthcare.

In the healthcare sector, the opacity of traditional machine learning models, especially in deep learning, raises concerns about the "black box" nature of these algorithms (Encarnação et al., 2022; Shaban-Nejad et al., 2020). In critical decision-making scenarios, understanding the underlying logic of AI-generated conclusions is necessary to foster trust (Lopes et al., 2022), ensure accountability, and address ethical considerations (Shaban-Nejad et al., 2020).

In recent years, there has been a surge in research focused on XAI, leading to extensive applications and deployments (Islam et al., 2022). Xu et al. (2019) identified three major stakeholders: users (clinicians) who interact with AI systems, individuals (patients) impacted by AI decisions, and developers responsible for creating AI systems and algorithms. For instance, consider a scenario where a medical practitioner relies on an AI system to generate diagnosis reports. By understanding the features within the input data that contribute to these AI-generated reports and comprehending the specific data points or characteristics that influence the AI's diagnostic decisions, healthcare professionals can make more informed and accurate clinical judgments, directly impacting the patient's care.

Transparency and interpretability in healthcare AI are vital for building trust among practitioners, ensuring patient safety, and facilitating informed decision-making (Encarnação et al., 2022). Nunes and Jannach (2017) draw a correlation between transparency and trust, suggesting that while the primary objective of the system's explanation facility may not be to cultivate trust directly, trust is anticipated to evolve as a natural consequence of transparency. Lipton (2018) Lipton suggests that trustworthiness may indicate confidence in the model's ability to perform effectively.

Ooge et al. (2022) suggest leveraging visual analytics to bolster trust among users, as it can provide insights into algorithms through visualisation, interaction, shepherding, and direct explanations. Alicioglu and Sun (2022) proposed two concepts: visual interpretation (VI) and visual-based explainable artificial intelligence (vXAI). VI refers to the use of visualisation techniques within an interactive framework to help end-users comprehend deep neural models without relying on XAI methods. vXAI, on the other hand, involves combining visual explanations with XAI approaches within an interactive visual interface, aiming to enhance the understanding of deep learning models.

1.6. Applications of XAI in Healthcare

Information visualisation and XAI applications in healthcare encompass various domains such as disease diagnosis, treatment recommendation, patient monitoring, and drug discovery (Encarnação et al., 2022; Islam et al., 2022; Manresa-Yee et al., 2021; Shaban-Nejad et al., 2020). Researchers have proposed various strategies to make AI models more explainable by employing comprehensible text (Lipton, 2018), mathematical approaches (Ali et al., 2023), or visualisations (Ooge et al., 2022). The following is a review of various applications in healthcare where visualisations have been used to make AI more explainable in the healthcare context.

1.6.1. Diagnostic Support

A prominent application of XAI in healthcare is diagnostic support, where AI models assist clinicians in interpreting medical images (Zeineldin et al., 2022), detecting anomalies (Lamy et al., 2020), and predicting disease risk (Wang et al., 2019). XAI techniques such as attention mechanisms (Ali et al., 2023) and feature attribution (Schlegel & Keim, 2021) enable the visualisation and explanation of AI-generated diagnoses (Liu et al., 2017), assisting clinicians in understanding the rationale behind AI automated decisions. Zeineldin et al. (2022) introduced the NeuroXAI framework for brain image analysis, incorporating explanation methods within visualisation attention maps to facilitate the diagnosis and detection of brain tumours in clinical contexts. Suh et al. (2020) created and validated a decision-support tool with XAI to estimate the probability of prostate cancer (PCa) and clinically significant PCa (csPCa) before a prostate biopsy. SHAP values helped explain the interactions and significance of each parameter (Suh et al., 2020).

1.6.2. Treatment Recommendation

XAI is also utilised in treatment recommendation systems, helping clinicians personalise therapy plans based on patient-specific characteristics, clinical guidelines, and real-time data (Deng et al., 2022; Krzysiak et al., 2022). By providing interpretable insights into the underlying factors influencing treatment recommendations, XAI enhances clinical decision-making and supports evidence-based practice (Nagendran et al., 2023). Lamy et al. (2020) developed a system for antibiotic treatment decision support using an ontology-based approach. They learned a preference model from clinical guidelines and visualised antibiotic recommendations using rainbow boxes (Lamy et al., 2020).

1.6.3. Drug Discovery

In drug discovery and development, XAI techniques offer insights into the relationships between molecular structures (Ponzoni et al., 2023), drug efficacy (W. Chen et al., 2023), corrective measures, explanation of system failures, mitigate potential bias and error prediction (Alizadehsani et al., 2023). This understanding enables various applications such as drug design and repurposing, virtual screening, protein design, side effects, reaction prediction, drug bioactivity, improved regulation and other tasks (Alizadehsani et al., 2023; W. Chen et al., 2023). The types of visualisation techniques used for drug discovery include heat map-based methods, colouring molecules methods, tree-based visualisation methods (Ponzoni et al., 2023), knowledge graphs, molecular graphs, convolutional neural networks, 3D-atomic coordinates, recurrent neural networks, graph neural networks, and other additional visualisation strategies (Alizadehsani et al., 2023; Deng et al., 2022). Stokes et al. (2020) leveraged deep neural network models to predict antibacterial compounds from large chemical libraries. The model identified halicin, a structurally distinct molecule, as a promising broad-spectrum antibiotic candidate, which was found to be efficacious in treating bacterial infections, including those caused by antibiotic-resistant bacteria (Stokes et al., 2020).

1.6.4. Patient Monitoring

Remote patient monitoring benefits from XAI-driven algorithms analysing biometric data from wearable devices (Mankodiya et al., 2022), including physiological sensors (J.-K. Kim et al., 2022), activity trackers (Ometov et al., 2021), smartwatches (Krzysiak et al., 2022) and mobile phones. Thus facilitating early detection of health issues, continuous monitoring for health assessment (Perez et al., 2019), personalised care (Krzysiak et al., 2022), sending alert messages to health services (Mankodiya et al., 2022), and predicting future health risks (Ometov et al., 2021). Time-series plots, heatmaps, scatter plots, SHAP plots, geographic mapping, and network graphs are among the visualisation tools utilised to depict patient data (J.-K. Kim et al., 2022; Mankodiya et al., 2022; Sure, 2023). Visualisation dashboards present insights and trends to healthcare providers, enabling proactive management of health conditions (Ploderer et al., 2016). Perez et al. (2019), using Apple ResearchKit (Apple Inc., 2024), developed a model designed to identify atrial fibrillation by analysing heart rate data collected from Apple Watches. The model provided visual explanations highlighting irregular heart rhythms as indicators of AFib (atrial fibrillation) (Perez et al., 2019).

Integrating XAI with visualisation techniques presents the potential to enhance healthcare by offering transparent and actionable insights derived from complex data sources. Applying XAI in diagnostic imaging, predictive analytics, drug discovery, and remote patient monitoring facilitates informed decision-making and personalised care.

1.7. Benefits and Challenges of XAI in Healthcare

XAI represents a noteworthy advancement within the healthcare domain, affording various advantages. Antoniadi et al. (2021) assert that XAI enhances decision confidence for clinicians, fostering hypotheses about causality and augmenting trustworthiness in the clinical workflow. Similarly, Das & Rad (2020) highlight that XAI has the potential to support specific rational reasoning processes and improve human workplace performance. Liao et al. (2020) and Wang et al. (2019) also emphasise that XAI's provision of diverse information and explanation types enriches decision confidence (and generates hypotheses for causality), mitigating decision biases and cognitive biases.

The incorporation of XAI into CDSs has yielded several benefits. Vorm (2018) explores XAI's usability and acceptability, illustrating its potential to provide different information types, render intelligent systems more explainable, and enhance overall acceptability and trustworthiness. Moreover, Das & Rad (2020) state that the advantage of some XAI visualisation techniques is that they support specific rational reasoning processes, enabling CDSs to bolster decisions with understandable interpretations for users with or without ML expertise (Das & Rad, 2020; Kunapuli et al., 2018; Vorm, 2018).

Notwithstanding the promising benefits, implementing XAI in healthcare encounters multifaceted challenges that necessitate judicious consideration and strategic solutions. A challenge in XAI is the task of transforming "black-box" AI and ML technologies into transparent, understandable solutions (Antoniadi et al., 2021; Das & Rad, 2020; Encarnação et al., 2022). Encarnação et al. (2022) emphasise the necessity of conveying trust and transparency to domain experts and end users. Antoniadi et al. (2021) delve into the challenges of implementing XAI in CDS, noting the absence of a universal definition of explainability and the subjective nature of interpretability.

Das & Rad (2020) highlight critical flaws in XAI visualisations and interpretability techniques, emphasising the need to reconsider using visualisation techniques for mission-critical applications. The trade-off between interpretability and performance introduces complexities in developing fully transparent models that balance local (explainability for an individual case) and global (explainability of the entire model, including its operational processes and decision-making mechanisms) explanations while enhancing accuracy and representations (Alicioglu & Sun, 2022; Saraswat et al., 2022). Nazar et al. (2021) also identified other key issues such as security, performance, vocabulary, evaluation of explanation, and generalisation.

In drug discovery, there is a need for sufficient and high-quality data, addressing dataset imbalance, and formulating hypotheses for drug design (Alizadehsani et al., 2023; Deng et al., 2022). Alizadehsani et al. (2023) found a lack of open-community platforms for improving model interpretations and sharing training data. Technical concerns include the effectiveness of molecular representations and the lack of standardised protocols (Deng et al., 2022). Alizadehsani et al. (2023) add that XAI techniques often require customisation for specific applications and a deep understanding of the problem domain to determine which model decisions require further explanation and what types of answers are meaningful to users.

Akrich (1992) examination of technology design brings to light a potential challenge in the context of XAI. Akrich (1992) focus on the dynamic interplay between designers and users reveals a crucial aspect: the anticipation of future users' interests, skills, motives, and behaviours, which is then embedded into the material technology through the creation of a "script" or "scenario." While this process allows for a representation of user interactions, the challenge arises in the potential discrepancy between the designer's projected user and the real user. Akrich (1992) emphasis on the continual back-and-forth interaction between these two entities during the iterative "description" process may introduce complexities in XAI applications. If the designer's assumptions about user behaviours deviate from the reality of user interactions, it could hinder the effectiveness and transparency of XAI systems (Akrich, 1992). Nunes and Jannach (2017) describe this distinction as perceived transparency (a user-perceived quality factor) versus transparency (an explanation purpose), suggesting that while the information presented to users may be perceived as illustrating the system's functionality, it may not always align with the system's actual operations. This is the issue with post hoc interpretability; while interpretations do not always elucidate how a system functions, they provide helpful information for its users (Lipton, 2018). This discrepancy raises concerns about the accuracy of user representations and the potential limitations in accommodating the diverse and unpredictable nature of real-world user behaviours within the design of XAI technologies.

The literature reveals a duality in applying XAI in healthcare, showcasing substantial benefits in CDS and increased confidence while grappling with challenges related to security, interoperability, uncertainties, transparency, and the interpretability-performance trade-off.

1.8. Technological and Research Trends

Current efforts concentrate on enhancing interpretability through techniques like feature importance analysis (Schlegel & Keim, 2021), local explanation methods (e.g., LIME, SHAP) (Dey et al., 2022), rule-based systems (Islam et al., 2022) and personalised explanations (Nunes & Jannach, 2017), while also emphasising model transparency through visualisation tools (Alicioglu & Sun, 2022; Ooge et al., 2022). Integration with clinical workflows is a key focus (Antoniadi et al., 2021; Ramalho et al., 2023), and continuous monitoring and feedback mechanisms are being developed to refine model performance over time (Encarnação et al., 2022; Mankodiya et al., 2022; Perez et al., 2019).

Research in XAI healthcare centres on fostering effective human-AI collaboration (Dey et al., 2022; Wang et al., 2019), addressing ethical and regulatory challenges (Islam et al., 2022), and tailoring XAI methods to specific healthcare domains (Dey et al., 2022; Krzysiak et al., 2022).

1.9. Future of XAI

Islam et al. (2022) advocate for a shift in the direction of XAI towards Responsibly Reliable-AI (RRAI), incorporating components such as ethics, compassion, sensibility, trust, and security to enhance acceptability and efficiency among human agents. This paradigm shift towards RRAI is deemed necessary to make XAI systems more acceptable and efficient in human-centred applications (Islam et al., 2022).

Nunes and Jannach (2017) highlight the need for further investigation into the relationship among stakeholder goals, user-perceived quality factors, and explanation purposes, emphasising the interrelated nature of these objectives. Additionally, exploring context-specific explanations tailored to user expertise and scenarios is important.

The current state of XAI in healthcare reflects a dynamic landscape characterised by rapid advancements, interdisciplinary collaborations, and ongoing efforts to address technical, ethical, and regulatory challenges. By fostering transparency, interpretability, and trust in AI-driven healthcare solutions, XAI is promising to revolutionise medical practice, enhance clinical decision-making, and improve patient care.

2. Values and design of technology

2.1. Human values and values in design

Human values encompass enduring beliefs regarding desirable modes of behaviour or end-states of being across various situations, societies, and cultural contexts (Rokeach, 1973, as cited in Iversen et al., 2012). Values are foundational principles that guide our actions, judgments and decisions and are intrinsic to our humanity (Iversen et al., 2012; Winter et al., 2018). Values may evolve and manifest (Manders-Huits, 2011; Van Der Weij et al., 2023) through the use and misuse of technology (Friedman et al., 2002; Harper, 2008).

The concept that technology can embody value is a notion that has been studied across multiple disciplines studying technology, society, and humanity (Flanagan et al., 2008; Friedman, 1997; Klenk, 2021; Winner, 1980). The defenders of the value-neutrality thesis, such as Pitt (2014), believe that "technological artefacts do not have, have embedded in them, or contain values". Pitt (2014) believes that human action ultimately determines the outcome rather than attributing moral responsibility directly to the artefacts themselves. Akrich (2006) challenges the notion that technology is separate from human values and highlights the importance of considering the broader socio-technical context in which technological artefacts exist and operate. Friedman (1997) states that technological features constrain or provoke human activity, yet they do not entirely determine it. Building on this idea, Klenk (2021) asserted that an artefact embodies value solely when facilitating valuable actions; thus, promoting such actions becomes justifiable. Miller (2021) introduces the Values-Principle, which suggests that if certain physical features of an artefact are required to perform a value-laden function effectively, then the artefact may be said to embody those values.

Verbeek (2014) argues that these artefacts possess a form of interactive moral responsibility, suggesting they are not value-neutral but are intrinsically linked with moral decision-making. Conversely, others suggest that technological artefacts can embody values independently of possessing moral agency (Brey, 2014; Flanagan et al., 2008; Kroes & Verbeek, 2014). Some believe that technological artefacts may influence people's values and inherently represent themselves (Klenk, 2021; Kroes & Verbeek, 2014; Winner, 1980).

There has been a growing emphasis on enhancing the user-friendliness of Information and Communication Technologies (ICTs) (Nielsen, 2000). The emphasis has primarily centred on improving the usability or the ease of use of technology whilst ensuring that the technology aligns with the values of its users (Fleischmann et al., 2015). In addressing potential ethical dilemmas associated with technology, scholars advocate for the early consideration of values during the design phase of new technological developments (Van Der Weij et al., 2023).

Given the role of human values in both the use and design of technologies, it is important to adopt approaches that systematically integrate these values into the design process. Value Sensitive Design (VSD) is a framework that acknowledges the inherent connection between technology and values while providing methods for addressing ethical and moral concerns.

2.2. Value sensitive design

In Value Sensitive Design (VSD), human values refer to what individuals and communities consider important and desirable in their lives, such as privacy, autonomy, fairness, and sustainability (Friedman et al., 2002). VSD also considers values in usability, conventions, and personal preferences (Friedman et al., 2002). These values are not inherent in the technology itself but are shaped by social, cultural, and ethical considerations (Friedman et al., 2002). It recognises that technological systems can have significant impacts on individuals, communities, and society at large. Therefore, VSD emphasises the importance of considering ethical and moral values in technology development (Cummings, 2006).

VDS is an approach to designing technology that integrates human values into the design process (Friedman et al., 2013; Poel & Kroes, 2014). Poel and Kroes (2014) identified three fundamental values inherent within the design process: the intended value, representing the designers' envisioned value; the embodied value, the value intentionally embedded within the artefact during design; and the realised value, reflecting the value that emerges during actual usage. In essence, VSD enables us to acknowledge the inherent value-laden nature of technology design, identify key decision points where values are relevant, analyse the values involved in specific design choices, and contemplate how these values should influence the design process (Schultz-Bergin, 2021).

VSD applies a tripartite method consisting of three investigations: conceptual, empirical and technical (Cummings, 2006; Friedman, 2004; Friedman et al., 2002, 2013). These investigations build upon each other iteratively, resulting in a cohesive artefact that embodies values in its design (Winkler & Spiekermann, 2021). Conceptual investigations delve into defining and analysing values, considering (direct and indirect) stakeholders' perspectives and societal impacts (Cummings, 2006; Friedman, 2004). Empirical investigations involve observing and measuring human interactions with technology and evaluating how stakeholders prioritise values and usability considerations (Cummings, 2006; Friedman, 2004). Technical investigations focus on the inherent properties of technology, exploring how they support or hinder human values and designing systems to align with identified values (Friedman, 2004).

An important consideration in VSD is determining the method for identifying which values to incorporate. Friedman et al. (2013) suggest thirteen key values essential for designing information systems, including human welfare, ownership and property, privacy, freedom from bias, universal usability, trust, autonomy, informed consent, accountability, courtesy, identity, calmness, and environmental sustainability. Borning and Muller (2012) and Le Dantec et al. (2009) argue against predefined value lists, advocating instead for a bottom-up approach to stakeholder value elicitation. Each approach has its strengths and weaknesses: while a predefined list may overlook context-specific values, bottom-up elicitation risks missing important ones if stakeholders cannot articulate them or crucial ones are overlooked (Umbrello & Van De Poel, 2021).

2.3. Value-sensitive design and AI / XAI

In identifying values in VSD for AI technologies, it is important to consider several factors. There is a growing consensus that the VSD list of values is inadequate for addressing the complexities inherent in AI systems (Le Dantec et al., 2009; Sadek et al., 2023; Umbrello & Van De Poel, 2021). Given the nature of AI, there is a need to adapt the existing list of values used in VSD to better suit the nuances of AI.

Le Dantec et al. (2009) and Umbrello & Van De Poel (2021) criticise the top-down VSD approach, which relies on a list of predefined values often imparted on technology. They argue that these values are hard to define across various contexts and may not be universal. Dantec et al. (2009) suggest a bottom-up approach, emphasising "value discovery" (Le Dantec et al., 2009) or value elicitation, defined as understanding the values within a specific context and designing with sensitivity to those values (Le Dantec et al., 2009), rather than prioritising known values or "frontloading" (Van Der Velden & Mörtberg, 2014). While other values should be considered in designing AI applications through bottom-up elicitation, it is essential to supplement any elicited list with principles to address typical AI ethical issues. It is proposed that AI for Social Good (AI4SG) meanings and principles be incorporated to ensure comprehensive ethical considerations in AI design (Umbrello & Van De Poel, 2021). In addition, Umbrello & Van De Poel (2021) suggests considering values identified by AI-specific entities, such as those listed by the EU high-level expert group on the ethics of AI, highlighting fundamental values including respect for human autonomy, prevention of harm, fairness, and explicability (European Commission, 2019).

2.4. Other methods of value assessment

In the field of design, the incorporation of values is important for creating products and services that resonate with users and contribute positively to society. While VSD provides a robust framework for integrating human values into the design process, exploring additional methodologies that assess stakeholder values is essential.

2.4.1. Contextual Inquiry

Contextual inquiry involves observing and engaging with users in their natural environment to understand their behaviours, needs, and values (Bird et al., 2021; Raven & Flanders, 1996). By immersing themselves in the user's context, designers can gain insights into the values that shape user experiences and preferences. Through interviews, observations, and participatory design activities, designers can uncover implicit and explicit values influencing user interactions with artefacts (Salazar, 2020).

2.4.2. Ethnographic Research

Ethnographic research involves studying cultures and social contexts to understand different communities' values, norms, and practices (Strudwick, 2021). To gain an understanding of a particular culture or group, ethnographers immerse themselves in the daily activities and behaviours of the subjects they study, documenting their observations along the way (Risku et al., 2022). By stepping inside the lives of users, designers are able to gain a deeper understanding of the values that are important to diverse groups of people and integrate these insights into their design process (Nawrocki, 2023). Designers can use ethnographic methods such as participant observation, interviews, and cultural probes to explore how values manifest in everyday life (Strudwick, 2021).

2.4.3. Mapping VSD onto AI4SG

This model extends traditional VSD to address challenges specific to AI by integrating AI4SG principles as design norms, ensuring transparency, explainability, accountability, and beneficence in AI systems (Umbrello & Van De Poel, 2021). The model employs a two-tiered approach to ensure values in AI technology design. The first tier involves a commitment to contributing to social good through AI, emphasising the importance of AI applications positively impacting society (Umbrello & Van De Poel, 2021). The second tier entails formulating and adhering to concrete AI4SG principles, which serve as ethical AI design and operation guidelines (Umbrello & Van De Poel, 2021).

Recognising the significance of contextual factors, the approach emphasises the interpretation of values within specific applications. Contextual interpretation helps identify the values at stake and facilitates the translation of relevant values into design requirements tailored to the particular context (Umbrello & Van De Poel, 2021).

This approach aims to mitigate ethical risks associated with AI technologies by incorporating AI4SG principles and contextual values into the design process. It emphasises the prevention of harm and actively contributing to societal good, addressing concerns about ethical "white-washing" and ensuring that AI applications align with fundamental ethical principles (Umbrello & Van De Poel, 2021).

2.4.4. Ethical Design

These frameworks focus on integrating ethical considerations into the design process. Ethical design involves considering users' and stakeholders' ethical values and norms (Leikas et al., 2019). It consists of identifying potential ethical issues, evaluating their implications, and making decisions prioritising ethical behaviour. Designers use the identified principles to guide their decisions and ensure their designs uphold ethical standards (Leikas et al., 2019).

Various expert groups and initiatives have proposed ethical principles to guide the development and use of AI. The Ethically Aligned Design Global Initiative (2016, 2017) proposes principles that prioritise human well-being, environmental sustainability, and the mitigation of risks associated with AI while emphasising the importance of aligning AI systems with societal values, respecting human rights, and ensuring transparency and accountability (2016, 2017). The Asilomar AI Principles (Future of Life Institute, 2017) were formulated to address the beneficial development of AI, highlight principles such as safety, failure and juridical transparency, responsibility, value alignment, human values, personal privacy, liberty and privacy, shared benefit and prosperity, human control, non-supervision; and avoidance of AI arms race. The European Group on Ethics in Science and New Technologies (EGE) (European Commission, 2018) proposed principles of human dignity, autonomy, responsibility, justice, equity, solidarity, democracy, the rule of law and accountability, security, safety, bodily and mental integrity, data protection and privacy, and sustainability. The European Commission's High-Level Expert Group on AI has formulated four principles based on fundamental rights that emphasise a human-centric approach to AI development, which includes respect for human autonomy, prevention of harm, fairness, and explicability.

Several other organisations and initiatives, including the Association for Computing Machinery (ACM) (Rossi et al., 2023), Google (Google AI, 2023), and the United Nations (United Nations System, 2022), have also introduced similar principles and guidelines regarding the ethics of AI.

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