

Towards a Greener AI Prompt

Exploring Environmental Impact Strategies and Design Requirements in a Hospital Setting



Name Student	Nihal Çinar
Student Number	621383
Supervisor	Erik van Raaij
Second Reader	Femke Hilverda
Case Holder	Sophia Children's Hospital
SKZ Supervisors	Sascha Verbruggen & Eris van Twist
Submission Date	22-06-25
Word Count	13364

AI Statement: While writing this master's thesis AI tools were used responsibly for brainstorming to support the structuring of content and to assist with the correct formatting of references in the references section.

Abstract

Background

The increasing consideration of AI technologies as a solution to problems in healthcare raises concerns about their environmental impact, especially in terms of energy consumption and data storage practices. Sophia Children's Hospital, as part of Erasmus MC, aims to approach these challenges while maintaining operational efficiency and high standards of patient care. This thesis aims to propose a value sensitive approach and explore strategies to optimize data practices to minimize the environmental impact of AI in Sophia Children's hospital.

Methodology

This study applies a Value Sensitive Design approach, conducting a conceptual, empirical and technical investigation. Within the technical investigation, both possible forms are conducted, combining a concept design for a sustainability assessment checklist intended for improving AI decision-making with a data lifecycle analysis evaluating the sustainability of current data practices at the hospital. These investigations are conducted through interviews with key stakeholders and an analysis of existing IT policies.

Results

The research has three main outcomes. First, by positioning sustainability as a key value alongside quality of care and operational efficiency, it defined corresponding norms and design requirements and structured them in a bi-directional value-norm-requirement hierarchy model. Embedding these requirements into AI design processes offers a way to address the complex value dynamics in hospital AI contexts. Furthermore, it developed a design concept for a qualitative sustainability checklist for AI, based on previously defined design requirements, to integrate environmental considerations into the cost-benefit analysis of AI systems, supporting context aware decision-making. Finally, a lifecycle assessment of AI data practices at Erasmus MC identified key inefficiencies in data practices. Actionable opportunities include optimizing data infrastructure through cold and warm data storage strategies, expanding FAIR data practices to enable more effective data reuse and engaging in federated learning initiatives to both minimize energy-intensive data transfers and ensure stored data is used optimally.

Conclusion

This research shows that sustainability is a growing interest within the field of AI in healthcare. A value sensitive approach towards AI can be achieved by conducting a qualitative AI assessment for the cost-benefit analysis and making improvements in current AI data practices. These findings contribute to the growing focus on AI in healthcare by offering a sustainable approach herein.

Table of Contents

Abstract	1
1. Introduction	4
1.1 Problem Definition	4
1.2 Relevance	4
1.2.1 Societal relevance	4
1.2.2 Scientific relevance	5
2. Research Objective and Research Question	6
2.1 Research Objective	6
2.2 Research Question	6
3. Theoretical Framework	7
3.1 Environmental Impact of AI Data in Healthcare	7
3.2 Value Complexity: a wicked problem	8
3.3 Baseline Values	9
3.4 Data Lifecycle Management (DLM)	10
4. Research Methods	12
4.1 Conceptual Investigation	12
4.2 Empirical Investigation	13
4.3 Technical investigation	16
4.3.1 Designing a value sensitive approach	16
4.3.2 Investigating the current system	17
5. Results	19
5.1 Value in AI Implementation	19
5.2 Quality of Care	22
5.2.1 Validation	23
5.2.2 Safe care	24
5.3 Operational Efficiency	25
5.3.1 Alignment with existing workflow	25
5.3.2 Reduction of (experienced) workload	26
5.4 Sustainability	26
5.4.1 Energy reduction	26
5.4.2 Minimizing waste	27
5.5 To Measure Is To Know	28
5.6 Sustainability in Practice	32
5.7 Data Lifecycle	33
Stage 1: Data creation	33
Stage 2: Data storage	35
Stage 3: Data use	36
Stage 4: Data sharing	37
Stage 5: Data archiving	38
Stage 6: Data deletion	39

6. Discussion and Conclusion	41
6.1 Conclusion.....	41
6.2 Key Findings.....	42
6.3 Limitations.....	43
6.4 Future Recommendations	45
References	48
Appendices	54
Appendix A: Topic lists	54
Appendix B: Code tree.....	62

1. Introduction

1.1 Problem Definition

Globally, Artificial Intelligence (AI) technologies are increasingly being proposed as solutions for healthcare challenges such as access, quality and efficiency of care (Suha & Sanam, 2023). For example, Sophia Children's Hospital (SKZ) in Rotterdam participates in initiatives like the Smart Health Tech Center (SHTC) as a part of the Erasmus Medical Center (Erasmus MC) (Erasmus Research Development Office, n.d., *About us*). Within such initiatives, activities surrounding AI-based technologies are developed, tested and integrated with the aim to continuously solve problems and improve care (Erasmus Research Development Office, n.d., *Strategy*).

However, while these AI technologies propose possibilities in healthcare, the neglect of their sustainability risks remains a critical issue (Lucivero, 2020). This is particularly concerning, considering that the environmental footprint of the data centers that support the functioning of AI is known to be large. According to Jia et al. (2023), the development of current computing ecosystems is incapable of keeping up with the exponential growth in resources, like data, required by AI models.

This growth in demand is reflected in the large volume, velocity and variety of produced and stored data (Austin & Kusumoto, 2016). Data has a constantly accumulating volume that rapidly increased by 50-fold between 2011 and 2020. Moreover, the variety of data results in 80 to 90% of data being unstructured, making it more demanding to store. Besides the abundance and variety of healthcare data another major obstacle is the large number of stakeholders. Despite its abundance, data remains fragmented across stakeholders, such as laboratories and hospitals. This results in redundant, underutilized and inefficient data storage, contributing to unsustainable data storage.

1.2 Relevance

1.2.1 Societal relevance

In 2023, the Dutch Ministry of Health, Welfare and Sport signed the Integral Care Agreement together with several healthcare parties, including hospitals, to prepare Dutch healthcare for the future by making it sustainable and appropriate (VWS, 2023). Two key principles of the agreement focus on the use of digital technologies: "Appropriate care takes place digitally if possible and physically if necessary" and "Appropriate care requires (digital and

technological) innovations that contribute to the social mission of making care people-oriented, sustainable and durable”. As a form of digital technology, AI is increasingly proposed within such innovations (Donins & Bahmane, 2023). On an international level, a United Nations (UN) document on the Sustainable Development Goals (SDG) proposes that collecting data can facilitate the “health and wellbeing goal” (Lucivero, 2020). Considering the increasing interest in AI the future of its implementation, the sustainability risks of AI and the data it requires become a crucial societal issue to address.

1.2.2 Scientific relevance

Research about AI often focuses on its advantages by presenting its potentials in societal development and problem-solving (Lucivero, 2020; Katirai, 2024). Consequently, an underexposed aspect of AI and its data sources remains their environmental impact. Research on optimal data storage and processing practices would therefore provide new and valuable insights on how hospitals can contribute to sustainability by minimizing their environmental footprint, while continuing to make scientific advancements through AI. Moreover, by examining the intersection of AI, sustainability and healthcare, this research will contribute to theoretical discussions on how technological advancements can be integrated in healthcare with environmental considerations, offering new perspectives on sustainable AI implementation.

2. Research Objective and Research Question

2.1 Research Objective

The aim of this research is to apply a value sensitive approach to AI and explore strategies to optimize data practices and AI-related decision-making to minimize the environmental impact of the increasing use of AI in the Sophia Children's hospital. Important boundary conditions in this objective are that the strategies should in no way compromise the quality of patient care or the operational efficiency of the hospital.

2.2 Research Question

The primary research question of this research is:

How can the Sophia Children's Hospital optimize AI-related decision-making and data practices to reduce the energy demand associated with AI without compromising patient care and operational efficiency?

The secondary questions are:

1. What do stakeholders of Sophia Children's Hospital consider crucial in data usage practices?
2. What would be the optimal balance of energy usage, quality of care and operational efficiency in design?
3. What is the energy demand of the data currently stored by Sophia Children's Hospital?
4. What are the current data storage processes at Sophia Children's Hospital?
5. What are the different ways of data storage and their energy consumption?

3. Theoretical Framework

To better understand data storage and processing practices, the theoretical framework explores the environmental impact of AI in healthcare and the wickedness of value complexity underlying healthcare sectors, including data systems. Furthermore, it will define three baseline values for data storage technologies in hospitals and explain Data Lifecycle Management (DLM) as a framework for the environmental impact of technologies.

3.1 Environmental Impact of AI Data in Healthcare

A crucial aspect of the environmental impact of AI in healthcare stems from its high energy consuming nature (Ueda et al., 2024). During the training phases, which refer to the initial process of teaching a model by using large datasets, AI models require large amounts of computational resources. This leads to high energy demands, likely provided by methods that emit large amounts of greenhouse gasses. Moreover, the need for large scale datasets and complex algorithms in combination with a repeated need for training further increase this energy demand (Ueda et al., 2024; Desislavov et al., 2023). Similarly, the inference phase of AI, which refers to using the trained model to make predictions or decisions on new data, shows a considerable use of energy and need for computational resources. While the costs of inference are often underemphasized in research due to its relatively smaller computational requirements, according to Desislavov et al. (2023) the costs of inference exceed training costs for deployed systems, due to repetitive use, making inference a crucial factor for the environmental impact of AI as well.

Moreover, additional elements related to the infrastructure of AI also contribute to its energy consumption. For example, as key pillars of AI infrastructures, data centers contribute significantly to the environmental impact of AI in healthcare (Ueda et al., 2024). The servers, cooling systems and network equipment in data centers use a substantial amount of energy. This energy demand stems from the need for constant operation and maintenance of optimal working environments for the equipment. For instance, the constant operation of data centers generates heat, which gets reduced through cooling methods, requiring additional energy to maintain optimal environments alongside the operational activities themselves (Zhang et al., 2021). While a 2020 article by Masanet et al. highlights that improvements in data center efficiency have led to a decrease in the energy use of data centers' infrastructure systems, including cooling activities, a 2021 study reports

that cooling systems alone still account for a considerable 30% of total data center energy consumption (Zhang et al., 2021). This suggests that despite efficiency gains, infrastructural elements, including cooling, remain a significant contributor to the overall environmental impact of data centers and consequently AI in general. The notions that data centers account for approximately 1% of global electricity consumption, that up to 30% of the stored data in the world is estimated to be related to health and the expected increase of the energy consumption of data centers leads to exacerbating expectations regarding the impact of AI on the environment (Ueda et al., 2024; Armoogum & Khonje, 2021).

An important consideration to make herein is that while indeed carbon emission is expected to increase due to the energy demanding nature of data used for AI, various elements can and do influence the intensity of this environmental impact. Factors such as the type and amount of data that is stored, the way in which it is stored and the storage period influence the storage requirements and therewith also the magnitude of its environmental impact (Smith, 2009; Samuel & Lucassen, 2022).

3.2 Value Complexity: a wicked problem

Healthcare sectors consist of complex systems, with value or normative complexity as a crucial aspect of this complexity (Cribb et al., 2022). The healthcare landscape contains multiple co-existing values. The complexity among these values arises from the notion that they cannot always be optimized simultaneously without challenging or conflicting with each other (Greenhalgh et al., 2023). In terms of healthcare improvements, specifically regarding sustainability of data storage, this normative complexity refers to the challenge of determining what is valuable and can be considered as an improvement for the healthcare sector (Cribb et al., 2022). Different stakeholders may have varied views of what should be prioritized in healthcare practices. These views on what 'good care' is, however, often conflict.

Given these value conflicts in healthcare improvement initiatives, particularly those aiming to improve the sustainability of data storage practices, this normative complexity can be classified as a wicked problem (Head, 2022). A wicked problem is a social problem involving multiple, often contradicting, perspectives on value (Rittel & Webber, 1973). It lacks a clear, collectively accepted solution. In the case of optimizing data storage to reduce its energy demand, different stakeholder, such as policy makers and healthcare providers,

may prioritize different aspects of change. The challenge of balancing these diverse values contributes to the wickedness of the sustainability problem in data storage, extending it beyond conceptual to normative complexity, which questions “what matters” in healthcare (Cribb et al., 2022).

Framing the optimization of AI practices as a wicked problem, one that requires balancing competing stakeholder values, supports a critical analysis of the trade-offs involved in implementing AI in hospital data infrastructures, as well as an analysis of various stakeholder views.

3.3 Baseline Values

An important consideration in defining the most crucial values within the normative complexity in hospitals is that optimizing data storage and processing practices is the leading strategy in the search for a more sustainable form of data storage. As the main goal of optimization is to improve overall sustainability, of which environmental sustainability is part, optimization and sustainability become inseparable concepts (Sadollah et al., 2020).

Within this leading strategy of optimization, reducing energy demand required for data storage is a central norm, as it is the main factor within environmentally sustainable technologies (Sadollah et al., 2020). In this determining role energy demand needs to be balanced with the availability of energy. Since current computing systems struggle to provide sufficient energy for the exponentially growing data, minimizing their energy demand is important for preserving energy sources and therewith contributing to sustainable development (Jia et al., 2020; Sadollah et al., 2020).

Beyond its environmental impact, optimizing data storage also affects different key hospital values, which must be considered in sustainability strategies. Michael Porter (2010) defines value in healthcare in a broader sense as outcome relative to costs. This ratio, emphasizing operational efficiency, suggests the importance of improving care outcomes while controlling costs. While Porter specifies costs in financial terms, costs can be explored further in different terms such as time and energy usage. However, this ratio of operational efficiency is nuanced by emphasizing value around patients (Porter, 2010). This nuance indicates that efficiency alone is insufficient without quality care. While a reduction of costs might increase efficiency its value remains deceptive without regard for patients.

Overall, the complexity of these norms arises from the co-occurrence of their interdependency and conflict (Greenhalgh et al., 2023). Environmental sustainability does not suffice as a value if it hinders operational efficiency. In turn the value of operational efficiency is limited without the complementation of quality of care, creating an interdependency between values (Porter, 2010). At the same time, however, these performance dimensions also struggle to co-exist and interact optimally. For example, to optimize patient care, one would want maximum quality for medical images, resulting in high energy demands for storage (Song et al., 2013). Efforts to compress images reduce this demand and contribute to sustainability but result in low reconstruction quality, leading to a trade-off between values. While designing a sustainable system, it is therefore important to balance the baseline values of energy usage, quality of care and operational efficiency in an optimal way.

This section operationalizes the theoretical wickedness of value complexity by identifying three concrete values (sustainability, operational efficiency and quality of care) that the study examines in relation to data storage and processing practices at Sophia Children's Hospital. It offers a lens through which to evaluate stakeholder priorities and technology trade-offs.

3.4 Data Lifecycle Management (DLM)

Finally, when considering the environmental impact of a technology it is vital to include a lifecycle perspective (Sadollah et al., 2020). As data volumes grow exponentially, organizations seek ways to manage its storage effectively (Reid et al., 2007). One approach the IT world particularly focuses on in this search is Data Lifecycle Management (DLM). This approach is believed to reduce complexity, inefficiency and inflexibility in data centers by categorizing data, including unstructured data, which forms 80 to 90% of healthcare data and is environmentally polluting as it is hard to store, based on its type throughout its lifecycle (Austin & Kusumoto, 2016; Reid et al., 2007). By increasing utilization and efficiency, this categorizing strategy reduces waste and helps optimize energy demand.

The data lifecycle consists of understanding different stages of data from its creation to its eventual destruction (figure 1) (Rahul & Banyal, 2020). Understanding this life cycle provides insights for managing challenges and prospects of data. The energy demand of data could for example be reduced by mapping and eliminating unnecessary processing and

storage, ultimately improving both operational and environmental sustainability by reducing energy waste and improving data governance.

DLM provides a practical framework to explore how energy efficiency can be improved throughout the stages of data usage in hospitals. This will guide the study in identifying specific opportunities for reducing energy demand without compromising care or efficiency.



Figure 1 Data Lifecycle (Rahul & Banyal, 2020)

Overall, healthcare is a sector dealing with the wicked problem of normative complexity (Cribb et al., 2022). Baseline values such as sustainability, operational efficiency and quality interact by complementing each other towards creating value while simultaneously challenging each other's preservation. The complexity arising from this type of interaction requires a balance between these values. A lifecycle perspective reveals the complexities arising between these values at all layers of the lifecycle. This insight helps designing an approach aiming towards sustainability while protecting the efficiency and quality of care.

4. Research Methods

To achieve the objective of optimizing AI and data practices in the Sophia Children's Hospital a design study will be conducted. The increased use of design thinking in addressing wicked problems, as is the case with the value complexity of sustainable AI and data practices, makes it particularly suitable for this study (Bender-Salazar, 2023). Specifically, the tripartite approach (figure 2) within the framework of Value Sensitive Design (VSD) will be employed. VSD is a design thinking methodology that not only aligns well with the case due to its sensitivity towards integrating values, such as environmental sustainability, into the designing process, but also because it was created for information technology design (Friedman et al., 2020; Friedman et al., 2008).

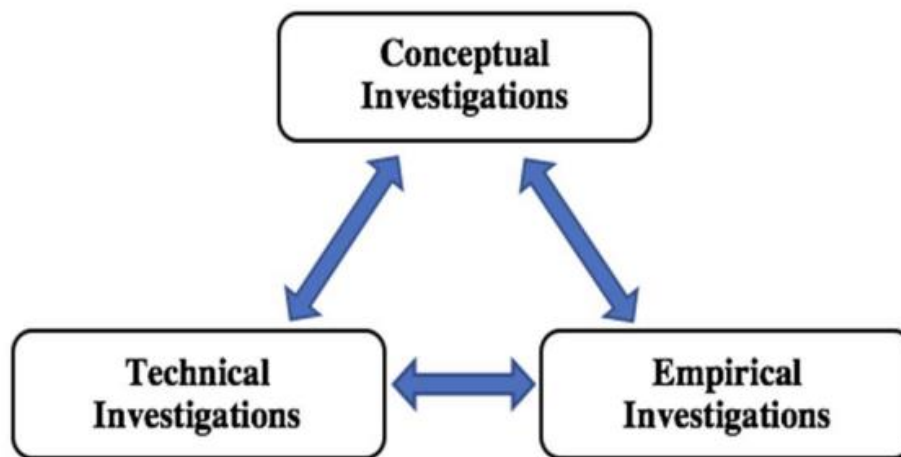


Figure 2 The tripartite iterative Value Sensitive Design methodology (Mithun et al., 2018)

4.1 Conceptual Investigation

The first part of the tripartite approach of VSD is conceptual investigation (Friedman et al., 2008). This investigation focuses on identifying and clarifying values that are required and therewith form the baseline of a design. A review of academic literature of value and AI in healthcare has identified sustainability, operational efficiency and quality of care as the main values of this research (Figure 3). This review, discussed in the introduction and theoretical framework, also highlighted energy reduction as the primary corresponding norm for sustainability.

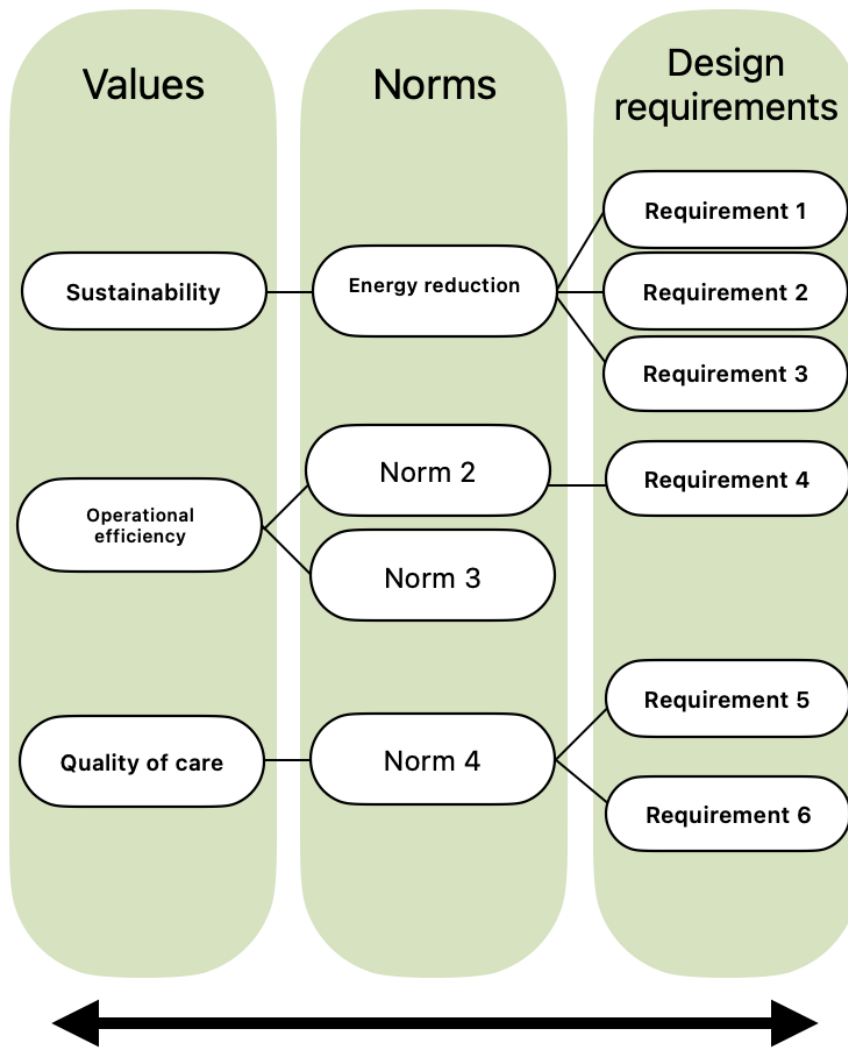


Figure 3 Bi-directional value-norm-requirement hierarchy. Adapted from (Longo et al., 2020).

4.2 Empirical Investigation

The second part, empirical investigation, explores how stakeholders perceive and prioritize the values and norm identified in the conceptual investigation (Friedman et al., 2008). For this exploration data has been gathered through one-on-one semi-structured interviews with healthcare providers, IT professionals, hospital managers, researchers and a medical ethicist, as can be seen in figure 4. The varying work areas of the selected respondents suggests data triangulation, specifically in the form of person triangulation, which entails collecting data from different respondents with varying perspectives, enhancing the validity and strength of the research (Tobin & Begley, 2010; Thurmond, 2001). Moreover, two of the respondents (3 and 5) came from a different hospital, Amphia Hospital, which helped increase the generalizability of the findings and supported data triangulation through space triangulation. The initial list of approached respondents was based on the recommendation of research supervisors from the case holder hospital. Later, the intranet and a snowball

method were used, in which some respondents and research contacts were asked to recommend others who could provide additional relevant information (Erasmus MC, 2025; Gierczyk et al., 2024). All respondents were approached via e-mail. Because of the respondents' preferences and for practical reasons all but one interview were conducted online. Finally, the interviews were conducted in Dutch.

In preparation for the interviews, a topic list (appendix A) was created using the theoretical framework from the conceptual investigation to develop sensitizing concepts. This topic list was reviewed and discussed with the supervisor before conducting the interviews. For ethical reasons, before each interview, permission to record the interview was asked to each participant in a clear and explicit manner. Moreover, each respondent was informed that they could withdraw from the study at any time and that their anonymity would be guaranteed. In the results section and data collection table (figure 4), the respondents have been anonymized and displayed in a way in which they are not directly retrievable. Furthermore, all approached respondents were interviewed on their perspectives on (sustainable) AI in healthcare and therewith have contributed to the empirical investigation stage of the research. So, while not every respondent is directly cited, all informed the interpretation of the research.

The data gathered from these interviews were recorded and subsequently transcribed using OpenAI's speech-to-text tool WhisperAI. While Whisper is considered as a valuable speech-to-text tool for research due to its high accuracy rates, the researcher also reviewed each transcript by comparing it with the original audio, increasing the validity of the tool by making sure it truly measured what it was supposed to (Naffah et al., 2025; Spiller et al., 2023; Ahmed & Ishtiaq, 2021). Moreover, WhisperAI offers the advantage that, unlike many language models, it does not require to upload data on remote servers for its processing activities (Spiller et al., 2023). Instead, these activities can be run locally on the computer, addressing privacy and ethical concerns of AI based transcription.

After transcribing, the data was organized by coding them through the method of open, axial and selective coding (William & Moser, 2019). The main themes that emerged from this coding process have been presented in a code tree in the appendices (appendix B). The analysis of the interviews involved investigating the perceptions of the stakeholders and the tension between possible value conflicts. Based on this analysis, personas were created to support the discussion on stakeholder perspectives with visual representations (figures 6-

8). Within these representations, for each stakeholder group, there is a short description of the stakeholder, the goals of the stakeholder, the needs of the stakeholder, the pain points that prevent the stakeholder from obtaining their goals and a quote from the interviews that provides clarification to the perspective of the stakeholder. The personas are presented in the result section. Moreover, the stakeholders' perception on how to address and secure their prioritizations contributed to determining the norms and requirements necessary for these securances and therewith helped completing the bi-directional value-norm-requirement hierarchy (figure 3) (Longo et al., 2020). Finally, the empirical investigation helped answering the first secondary question.

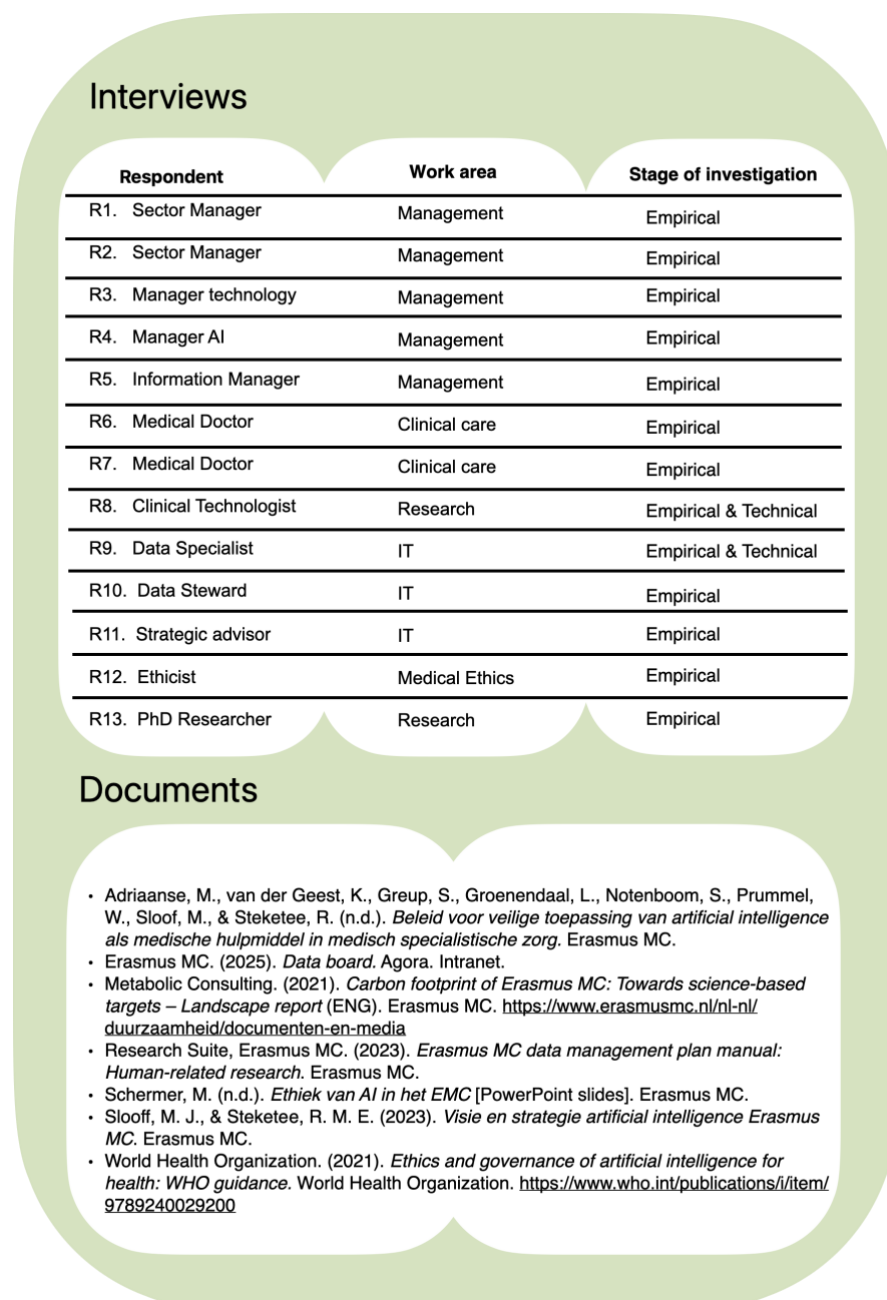


Figure 4 Data collection

4.3 Technical investigation

The technical investigation consists of two possible forms (Friedman et al., 2008). One form focusses on proactively making a design that supports the values identified in the conceptual investigation. The second form focusses on how features of existing systems hinder or support the human values, in this case specifically sustainability. In this research both forms of technical investigation have been addressed, with one fully conducted and the other explored in part.

4.3.1 Designing a value sensitive approach

The first form of technical investigation that was conducted focusses on designing an approach to proactively include values in the IT practices of the Sophia Children's Hospital (Friedman et al., 2008). This has been done by the researcher in a four-step process (figure 5). In the first step requirements were defined for the design (Van Aken et al., 2007). For this the design requirement gathered in the empirical investigation were used. Additionally, multiple stakeholders expressed the wish for sustainability to be included in a cost-benefit analysis during the interviews, which was incorporated as an additional design aim. Combining the design requirements with the design wish created a holistic list of boundary conditions and requirements for the design. Then, potential solutions have been explored for the problem. This process has been conducted in a theory-informed way by first exploring quantitative approaches and finally opting for a qualitative approach after evaluating the potential approaches based on the design requirements and their feasibility, completing step two and three of the four-step process (Van Aken et al., 2007). After choosing for a design option an initial design concept has been created based on the design requirements for sustainability. This preliminary prototype has been presented through a visual representation (figure 11) to be further explored and developed in further research. During these processes the second research question was addressed.

Four-step design process

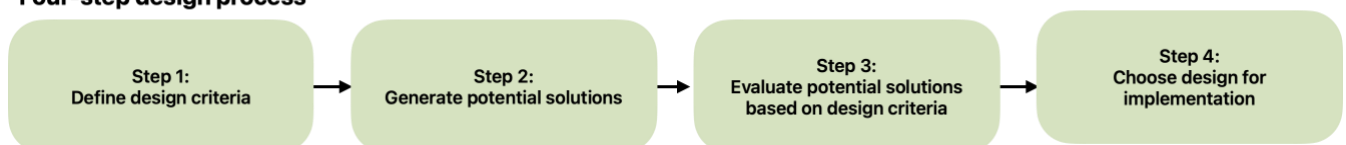


Figure 5 Design process. Based on (Van Aken et al., 2007)

4.3.2 Investigating the current system

During the second part of the technical investigation the existing practices and technological infrastructure have been investigated by first exploring the current practices and energy demand of the data currently stored and then by mapping out the data lifecycle in the Sophia Children's Hospital, answering research questions 3, 4 and 5. In line with the findings on the current energy demand, a value-informed exploration of the data lifecycle of SKZ was conducted complementary to the qualitative checklist prototype from the first part of the technical investigation. While the checklist prototype focuses on guiding decision-making before implementation, the lifecycle assessment aims to understand and improve existing practices across the AI lifecycle, offering additional suggestions for improvement. Since the data practices of SKZ are in line with those of Erasmus MC as a whole, this exploration included the entire organization. The lifecycle stages were examined from creation to destruction. For each stage, the current practices were assessed alongside their sustainability implications. Then, an evaluation was made to determine whether anything can be done to make these practices more sustainable. Finally, specific recommendations and ideas for future research to support more sustainable practices throughout the stages of the lifecycle (figure 1) have been given in chapter 6. The information for the energy consumption and lifecycle assessments was gathered by collecting documents on the IT and data policies of the hospital (figure 4). Additionally, besides the empirical interview, a separate semi-structured technical interview has been held with the data specialist (respondent 9, figure 4). The topic list for this interview can be found in appendix A. While no separate technical interview was conducted with the clinical technologist (respondent 7, figure 4) due to the respondent's busy schedule, the interview had a substantial technical focus as well. The insight from these interviews were used to further complement the analysis of current practices and infrastructures of the case holding Sophia Children's Hospital. The transcripts of the two interviews have been coded with the same open, axial and selective coding strategy as in the empirical investigation (William & Moser, 2019). A comparison between current protocols and experienced practices helps depicting the data lifecycle from a theoretical and practical point, making it more holistic. Moreover, the use of multiple types of data leads to data triangulation, which helps increasing the credibility and validity of the research (Bans-Akutey & Tiimub, 2021).

This chapter outlined the use of Value Sensitive Design as the leading methodology of this research. It described the use of conceptual, empirical and technical investigations to explore and support sustainable data practices at the Sophia Children's Hospital. Through literature and interviews stakeholder values were identified and translated into design requirements. These were then used to guide the development of a value-sensitive concept design and in combination with a document analysis to analyze current technological practices. Each methodological step contributes to answering the five secondary research questions.

5. Results

This chapter presents the results of the research and is structured around the empirical and technical investigations. It builds on the conceptual exploration conducted in the introduction and theoretical framework. The chapter first presents the empirical investigation, starting with the stakeholders' general perspectives on the value of AI. Then, for each core value, quality of care, operational efficiency and sustainability, specific norms and design requirements are identified based on the interviews.

This is followed by the technical investigation, which first explores how sustainability can be integrated into AI-related decision-making, leading to the development of a preliminary design concept based on stakeholder input. This is followed by a second form of technical investigation, which analyses current AI and data-related sustainability practices within Erasmus MC through internal documents, strategies and carbon footprint data. The chapter concludes with a lifecycle analysis that evaluates the environmental impact across different stages of the data lifecycle.

5.1 Value in AI Implementation

Understanding which values should guide the implementation of AI in healthcare is essential for making responsible design choices and is a central focus point for various stakeholders within healthcare. For the stakeholders, in the conversation of AI, the main discussion revolved around what the additional value of various AI tools should or could be for the hospital. Two prominently recurring core values, which the stakeholders expected to function as the main potential value of AI, were quality of care and operational efficiency, creating a parallel with the values appearing in the theoretical exploration of the normative complexity in hospitals (chapter 3.3). A crucial point herein, however, remains to be the word "potential". As the AI manager emphasizes there is a strong sense that AI in healthcare is not a passing trend but a development with true potential. *"Of course, we all see the potential and it will definitely happen. That is also why we are so busy with it. Otherwise, we would have dropped it already"* (respondent 4). This quote reflects the widely shared belief that AI is a transformative force worth investing in. However, this belief does not mean stakeholders are uncritical. While the respondents see actual opportunities, especially for improving operational efficiency and quality, they also acknowledge that not every problem requires an AI solution. Several respondents noted that AI is often proposed in situations

where simpler alternatives would be more suitable. This suggests the need to evaluate if AI adds real value, rather than assuming its usefulness directly. As one stakeholder critically remarked: *“The disadvantages are, I sometimes call it the AI hammer, everything these days has to be solved with an AI solution, that is the idea”* (respondent 4). The metaphor of the AI hammer shows a concern that AI is sometimes used as the automatic solution for everything, even when the problem does not really need such a complex solution. A concrete example is when an AI solution was proposed for a problem that eventually could be solved with a *“chess clock”* (respondent 4). Another expert expressed a similar view, emphasizing the need to look deeper:

“A disadvantage I think is that... it is used a bit like a band-aid. Something does not work so well, so we stick an AI band-aid on it and then it works a bit better. While you actually have to take a step back and look at the underlying problem and solve that. Because it is a pretty expensive and complex band-aid” (respondent 10).

Together, these remarks highlight the importance of carefully assessing whether AI is truly the best solution for a particular problem instead of automatically opting for it. Moreover, this sentiment is echoed by literature on absolute sustainability, which underscores the importance of questioning if an AI tool is a necessity or not (Heide & Gjerris, 2024).

Another important notion is that while quality of care and operational efficiency were shared as core values for such an assessment across the stakeholders, some individuals emphasized certain values more strongly. As illustrated in the stakeholder personas (figures 6-8), medical professionals emphasized the importance of quality of care more. One doctor, for example, noted that even while they personally value sustainability, their professional responsibility as medical professional means that quality of care will always outweigh other values in their care delivery. This highlights that professional roles and responsibilities can shape the way in which values are prioritized in practice, even when there is support for multiple values, reinforcing the complex and sometimes conflicting nature of co-existing values.

Frame 1: Stakeholder personas

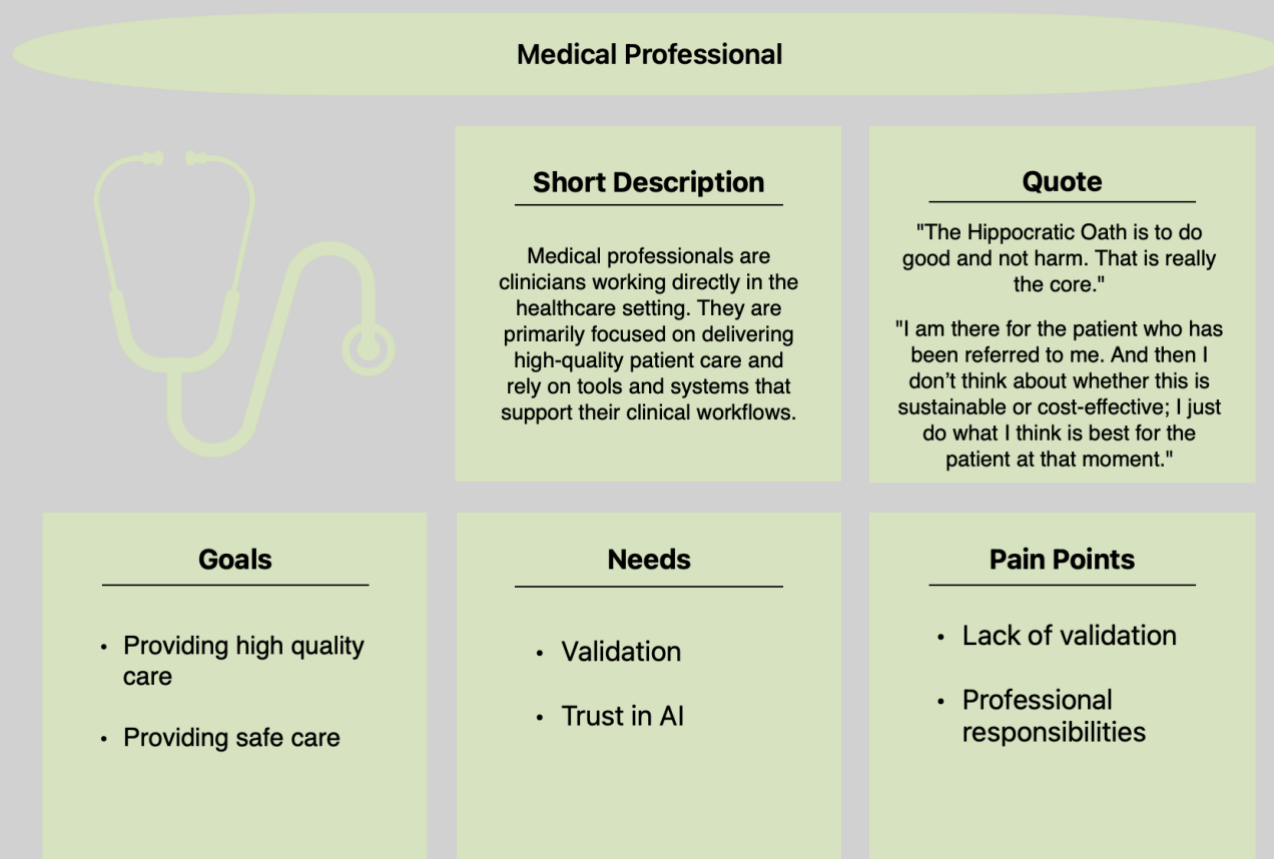


Figure 6 Persona Medical Professional

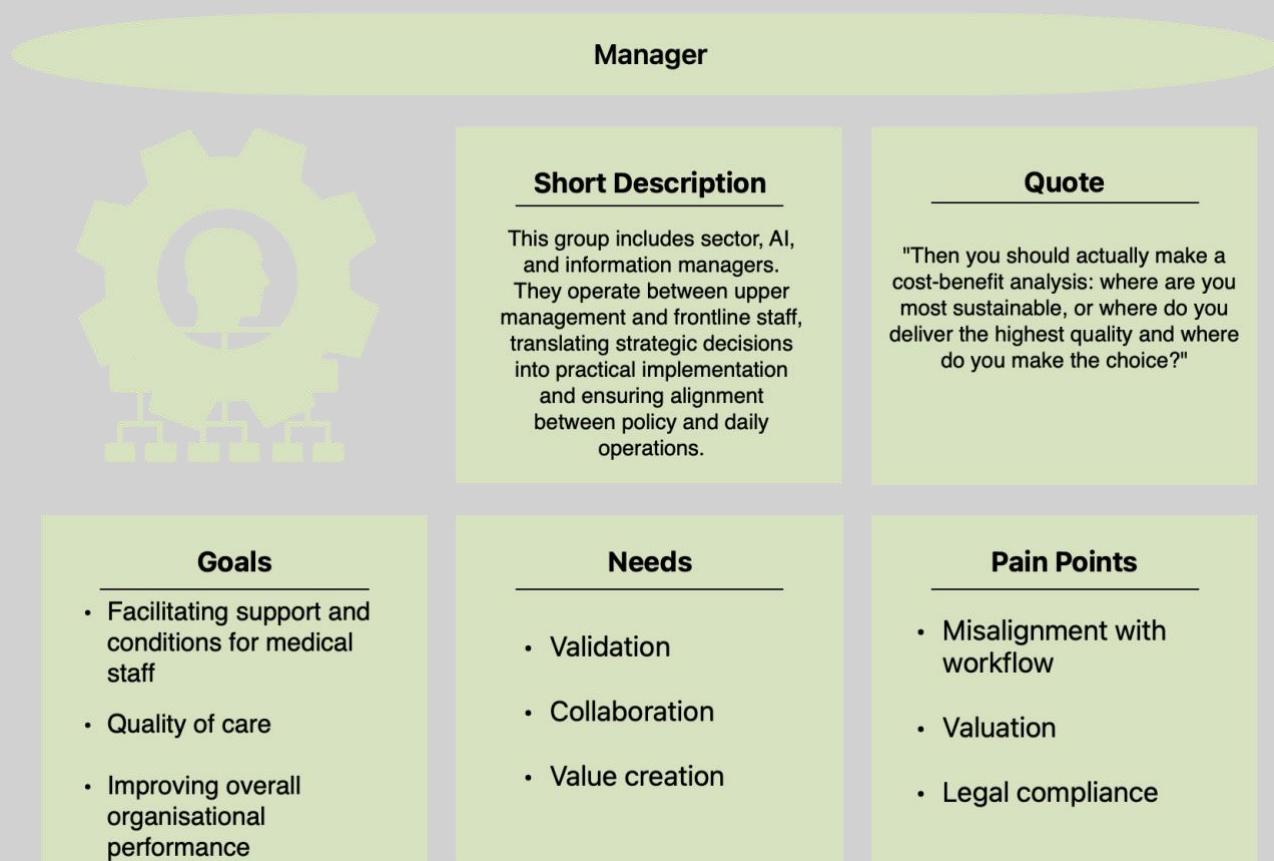
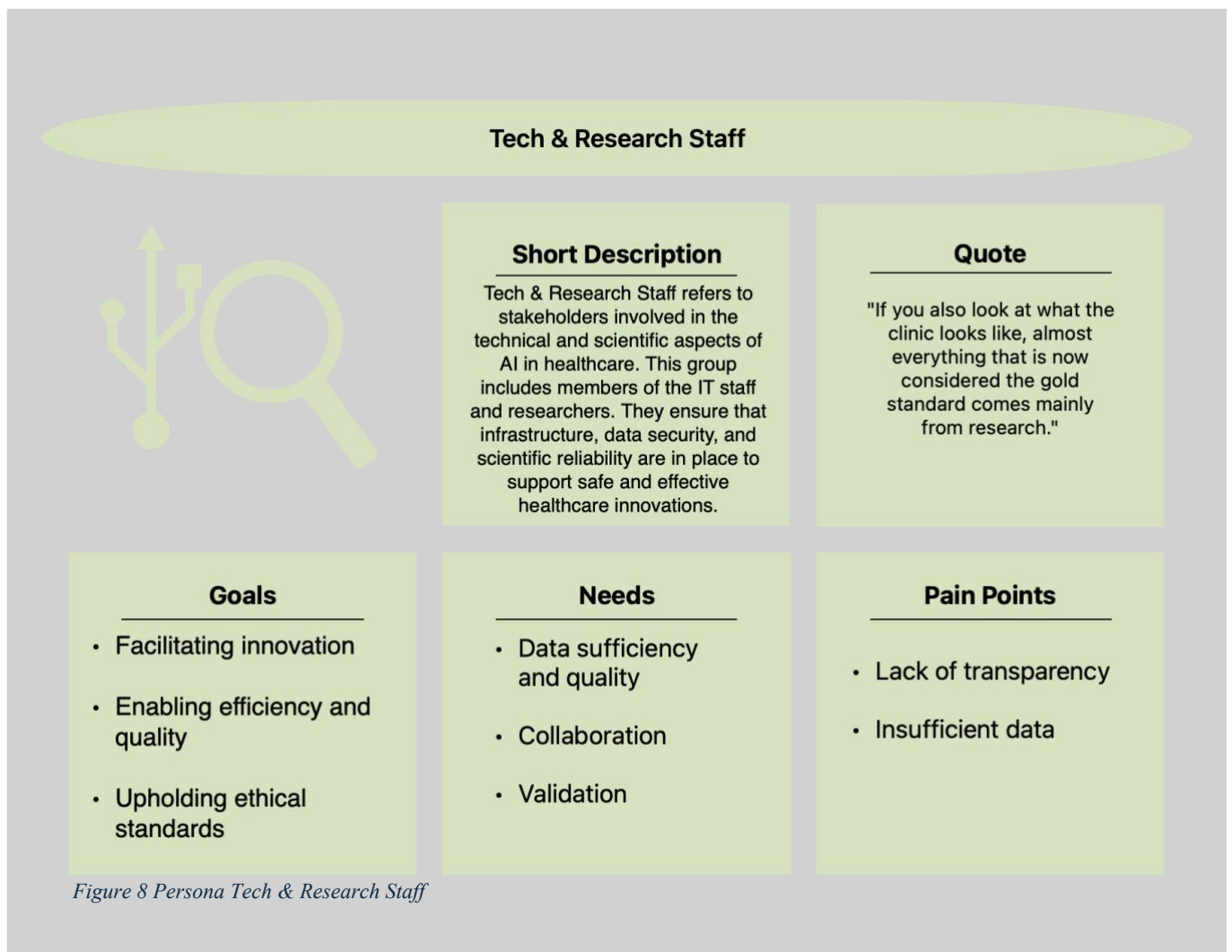


Figure 7 Persona Manager



5.2 Quality of Care

Due to the central role quality plays in healthcare, it is crucial to explore how this value translates into concrete norms and design criteria for AI implementation (figure 9). For stakeholders, particularly medical professionals, quality of care was often prioritized over other values. Since sustainability efforts in healthcare must be embedded in this quality-driven context, it becomes important to understand how quality considerations can be made.

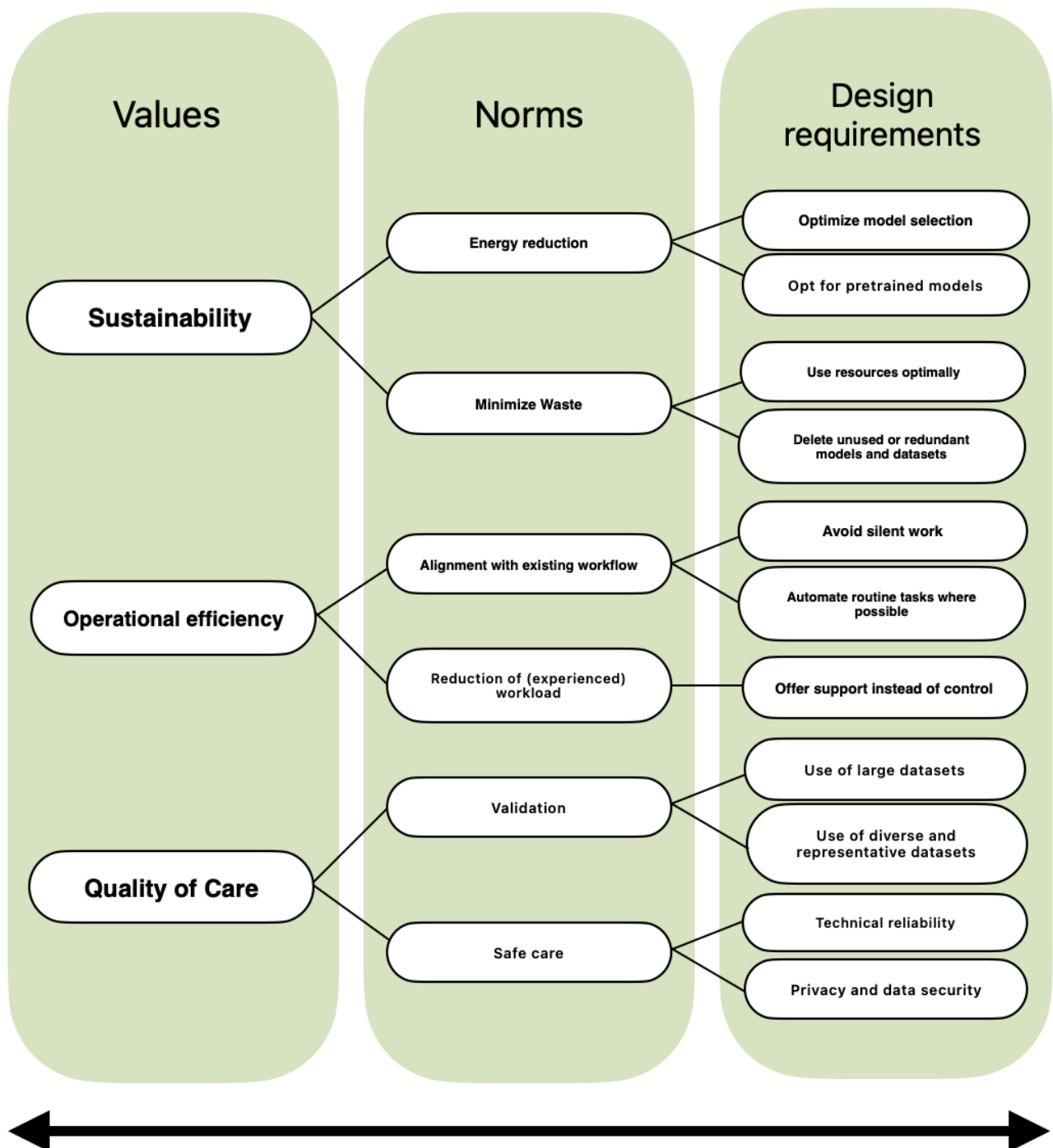


Figure 9 Bi-directional value-norm-requirement hierarchy. Adapted from (Longo et al., 2020).

5.2.1 Validation

An important aspect of AI in relation to the core value of quality is its validation (figure 9). The reason validation seems to be especially important for ensuring quality, according to respondents, is because of the sensitive nature of the healthcare sector. One respondent illustrated this by comparing the healthcare sector with a commercial setting, explaining that when internet service center makes a validation mistake in their service one might just

switch to another provider. *“No one dies”* (respondent 9). But in a hospital context the risks of validation shortcomings are more significant:

“An engineer creating an AI model might think, wow, 90% accuracy, that is great! But for a doctor, that 10% in a population they see frequently might still result in a large enough number of patients where things go wrong or might go wrong” (respondent 8).

These comparisons clearly illustrate that validation of AI is especially important for upholding quality in a healthcare setting as the severity of its consequences are high.

Given the importance of validation, it is crucial to establish design requirements necessary for validation. Respondents highlighted the importance of data within validation. As the clinical technologist suggests: *“A model performs as well as your data”* and adds *“often you only have data from one type of population or from one department in one hospital and the moment you test on a dataset that was collected at a different time or different location, it plummets”* (respondent 8). This directly suggests the use of diverse and representative datasets as an important requirement for validation and bias reduction (figure 9). Additionally, the need for large datasets is emphasized as another crucial design requirement (figure 9). As noted: *“Especially if you want to use AI, you need a lot of data”* (respondent 8). This highlights that having a sufficiently large and varied dataset is key for ensuring that the AI model performs reliably.

5.2.2 Safe care

Besides validation another prevailing norm for qualitative care is safe care (figure 9). As AI becomes more integrated into healthcare processes, it is vital that it does not cause harm and consistently operates safely. A medical specialist states: *“I think that if you have developed an AI tool, you still need to properly investigate whether it truly benefits the patient and is actually safer”* (respondent 6). This underscores that safety cannot be assumed based on validity alone, it must be demonstrated through careful evaluation and implementation. The first design requirement for safe care is technical reliability. One respondent gives an example of a validated system making major errors after the medical documentation system it relied on for data was updated, illustrating the importance of being able to rely on the AI system. Another crucial aspect and requirement for safety is privacy and data security. An important requirement across the different stakeholder profiles was privacy for the sensitive medical information.

5.3 Operational Efficiency

Having explored what norms and design requirements quality of care requires for responsible AI use, it is equally important to consider the value of operational efficiency (figure 9). This value was frequently emphasized by stakeholders as one of AI's main promises, particularly in reducing administrative burdens.

5.3.1 Alignment with existing workflow

A recurring theme in the interviews was that AI should not disrupt but support existing workflows. As one respondent explains: *"We did a full evaluation, we looked at where in the clinical workflow we wanted to implement it"* (respondent 4). This approach highlights alignment with the existing workflow as the first norm of operational efficiency (figure 9). For AI to be effective in practice, it must be designed in a way that fits well into healthcare professionals' routines. This idea is supported by a medical professional stating: *"You can have a fantastic algorithm, but nurses, care providers and doctors have to learn to work with it and also gain confidence in it"* (respondent 6).

A major part of incorporating AI into the workflow is by automating current tasks. As one respondent says: *"You can automate that. Reliable results come out. Yes, then you have efficiency"* (respondent 6). This comment shows that efficiency is not just about doing things faster, but also about taking over routine tasks in a reliable way, so professionals can trust the results and use them with confidence. The types of routine tasks that are considered suitable for automation are primarily non-nursing tasks, such as administrative duties or diagnostic scoring. Another crucial requirement to seamlessly incorporate AI into the workflow is by avoiding silent work, which in this research refers to informal and unseen tasks that emerge after the implementation of an AI tool. This aligns with the invisible work Hampson and Junor (2005) aim to highlight through the concept of articulation work, particularly in technology driven jobs. According to a respondent: *"Sometimes you actually see that it creates more work, because more information is generated and people have to assess or process more things or handle them differently"* (respondent 4). This remark highlights that while efficiency can be intended by automating tasks with AI, true alignment with the workflow requires attention for avoiding silent work as well (figure 9).

5.3.2 Reduction of (experienced) workload

Another crucial remark made in the discussion of efficiency relates to the experience of workload. Besides quantified workload, the load of the work one performs has a subjective aspect to it. Even when AI automates certain tasks, it can still increase the perceived workload if it adds pressure to daily routines. This highlights the importance of designing AI that not only takes over tasks but does so in a way that decreases the experiences burden of it. A key design requirement herein is that AI should act as a supportive tool rather than a controlling mechanism. Various stakeholders emphasized the importance of maintaining control over one's work through a sense of autonomy and professional judgement. When AI systems allow room for clinical intuition and do not reduce professionals to mere executors of algorithmic suggestions this could reduce stress.

5.4 Sustainability

While quality of care and efficiency were the most prominent values the stakeholders associated with AI implementation, they also considered value in a broader sense, with sustainability becoming increasingly included in this perspective. One way in which sustainability is aimed to be incorporated as a value is through policy. One manager for example aims to include sustainability as an ethical aspect within the cost-benefit assessments, which would be used as a policy tool before implementing AI: *"Then you should actually conduct a cost-benefit analysis to determine where you are most sustainable or where you get the most quality and where you make the choice"* (respondent 2). This illustrates the growing awareness that decisions about AI are not only technical or financial, but also involve ethical trade-offs between values like sustainability and quality of care.

5.4.1 Energy reduction

As was already identified in the conceptual investigation phase and confirmed by the interviews, an important norm for sustainability in the context of AI is energy reduction (figure 9). The first and most evident design requirement for energy reduction is optimizing model selection. Expressions like *AI band-aid*, *AI hammer*, *buzzword* or AI being used *willy-nilly*, as used by the interviewees, illustrate how AI is increasingly becoming the default solution in healthcare. A collectively proposed requirement to elevate the environmental cost of this tendency is to adopt a more critical approach in selecting which AI tools or models should be implemented and which problems truly require an AI solution. A second

approach is to opt for pretrained models rather than developing new ones from scratch when possible. While Erasmus MC, including Sophia Children's Hospital, as an academic institution, has in-house expertise that allows for the development or fine-tuning of AI models, training large models entirely remains energy intensive and is not always necessary. Instead, adapting existing models is a more manageable and sustainable option. As one respondent explained: *"So we mainly focus on whether a model is manageable, retrainable... and whether we can monitor its quality. So I think we are really asking ourselves: are we going to build this ourselves, or should we just buy it?"* (respondent 9). This reflects a strategy to weigh sustainability, manageability and quality when deciding whether to train models or adopt external solutions.

5.4.2 Minimizing waste

The second norm for sustainability is minimizing waste, particularly in terms of data (figure 9). A key design requirement for this norm is the deletion of unused or redundant datasets and models. Data and models that are no longer necessary can lead to unnecessary storage costs and increased energy consumption for maintaining these resources. Data management involves regularly assessing whether datasets and models are still relevant and necessary. As a data specialist emphasized: *"We are also not very critical about, 'Do we really still need this? Let us throw it away' "* (respondent 9). This highlights the need for a more critical approach to managing data to ensure that only essential resources are used and the environmental footprint of AI systems are limited.

The second design requirement for minimizing waste is optimizing data efficiency. While improving data efficiency may not directly reduce absolute energy consumption or pollution, it allows to get more value from the data, which means that the energy used for storage and processing is not wasted. Though respondents did not explicitly mention data efficiency, they highlighted the importance of collaborating to optimally use resources and knowledge. For example, one respondent noted: *"Because on your own... it just takes longer to achieve that"* (respondent 7). This emphasizes that working together more efficiently can help avoid wasting resources and maximize the value generated from available data. Furthermore, the idea of optimizing data efficiency is supported within the framework of Green AI. In this framework Schwartz et al, (2019) advocates for computational efficiency to be increasingly considered as a way to measure and improve the sustainability of AI models.

By optimizing data usage, hospitals can ensure that AI solutions are not only more sustainable but also more impactful, maximizing the value gained from the data and knowledge they already possess.

5.5 To Measure Is To Know

After identifying the core values, norms and design requirements associated with AI the next question that occurs is how the impact of AI models on these values can be measured. In line with this, several respondents emphasized the importance of conducting a cost-benefit analysis in which key values, including sustainability, are explicitly taken into account. Quantifying the environmental impact of AI is also emphasized in literature, with the suggestion that it would contribute to approaching impact minimization through transparency (Dodge et al., 2022). Moreover, it is specifically suggested to incorporate sustainability as a metric into cost-benefit analyses, in the same way financial costs are currently considered, mirroring the respondents' desired approach (Lannelongue & Inouye, 2023).

While the stakeholders have expressed a clear intention to integrate sustainability into AI decision-making and even include it in policy, the question remains: how should sustainability be evaluated and weighed? As one respondent reflected:

“Because we have indeed stated in our policy that one of our guiding principles is to take sustainability into account when deciding whether to implement an AI solution. But then I get a question in return, and it is a valid one, ‘Yes, but how do we actually determine that?’ And at this moment, I do not really have a definitive answer... So I’m genuinely curious whether there are sustainability assessments we could use to include this in the decision-making process” (respondent 4).

This underscores a broader challenge created by the lack of established methods to assess sustainability in AI. The same respondent added: *“I think we have not really quantified the ecological footprint very well at this point”* (respondent 4). This illustrates a quantitative approach towards assessing sustainability. Within the scope of quantitative assessment there are multiple available measures that can be applied. Herein it is important for the hospital to determine what measure is most desirable for them. Some common quantitative measures for evaluating the environmental impact of AI models are presented in Figure 10, alongside their pros and cons. Using these metrics the hospital can execute a comparison

between models. A suggested approach by a stakeholder was to create a ranking system, mimicking AI ranking systems, such as LiveBench.ai, which benchmark AI models on performance metrics (Livebench.ai, n.d.).

Measure	Description	Pros	Cons
Carbon Emission	Estimates CO ₂ released during model training or execution.	• Directly reflects environmental impact.	• Highly dependent on local electricity infrastructure • Not comparable across locations/times
Electricity Usage	Tracks power consumption of hardware components	• Correlates with carbon emissions • Some hardware supports detailed tracking	• Hardware dependent • Limits fair comparison between models
Elapsed Real Time	Measures total runtime for a task or model process.	• Simple to obtain • Suggests computational effort	• Affected by hardware, background activity and system workload • Hard to compare across systems
Number of Parameters	Counts total (or learnable) model parameters.	• Hardware-independent • Correlates with memory use and complexity	• Not all parameters are used equally. • Does not reflect actual computation done.
FPO (Floating Point Operations)	Estimates the total computational work	• Independent of hardware • Correlates with energy use and runtime • Allows fair comparisons	• Not widely adopted • Tooling still incomplete in some libraries

Figure 10 Environmental Impact Measures for Computational Models, based on Schwartz et al. (2019).

However, even after determining a measure, quantifying impact for cost-benefit analyses remains difficult. To include sustainability in a cost-benefit analysis and therewith make informed decisions, sustainability should be assessed a priori, before an AI tool is developed or implemented. As became evident from the interviews, AI in healthcare is still an emerging field and tools are often in the early stages of development or even conceptual. As a result, it is difficult to estimate environmental impact before the tool exists. Without a functioning prototype, there is no model to test, no code to run and therefore no impact to quantify. This means that despite the stakeholders' and scholars' emphasis on the importance of better estimates on the environmental impact of AI, data scientists have no reliable access to this information (Dodge et al., 2022). This makes it challenging to include sustainability in the early phases of decision-making, despite its recognized importance.

Given the limitations of the quantitative metrics, it is important that the hospital selects a measurement approach that aligns with its values and understanding of sustainability. Whether that be minimizing energy use, limiting the carbon footprint or something else. However, due to the shortcomings of each measure and the difficulty of obtaining them a priori, an entirely quantitative approach is unlikely to provide a complete assessment, based on which decisions can be made. Therefore, ideally, the hospital should complement it with a qualitative sustainability assessment. Such an approach allows for flexibility and to contextualize the assessment on the specific hospital, especially in the early stages of AI development when concrete data is often unavailable. A systematic review of artificial intelligence impact assessments emphasizes that a core component of AI impact analyses consists of a checklist including, among other things, sets of ethical questions and sustainability principles (Stahl et al., 2023). As a respondent from the Amphia hospital noted as well: *“That is often not substantiated with numbers, either because we do not have the metrics or because it just... you know, our ward is busy too. So then measuring the benefits is actually quite subjective”* (respondent 13). This shows the need for a more practical and adaptable way to assess sustainability, especially when quantitative data is not available.

To ensure that sustainability considerations are incorporated into early-stage decision-making in a qualitative way, the hospital could adopt the checklist approach. Moreover, this checklist could be complemented by adding assessment criteria for different values such as efficiency and quality of care. An initial design concept that could work as a foundation is presented in figure 11. The questions in this checklist are based on the design requirements for sustainability, as identified in the bi-directional value–norm–requirement hierarchy developed in this research (figure 9). As these requirements emerged from the value discussions in the interviews, the questions informed by them reflect a value-sensitive approach. Moreover, while the checklist is primarily qualitative as it guides reflection and raises awareness instead of calculating precise outcomes, it can be made semi-quantitative by adding scores to each item and creating a total sustainability score that can be added to a cost-benefit analysis.

Sustainability Readiness Checklist for AI in Healthcare

Purpose: assessing sustainable design choices for AI applications in hospital settings.

Model Development

Questions	Answer Options	Score / Comment
Was the model developed based on an existing (pre-trained) model?	☐ Yes ☐ No ☐ Unknown	
Was a smaller or more efficient model considered?	☐ Yes ☐ No	
Was a less complex alternative (non-AI) solution considered?	☐ Yes ☐ No	
Can the model be reused in different departments?	☐ Yes ☐ No ☐ Partly ☐ Unknown	
How often is the model retrained?	☐ Weekly or more ☐ Monthly ☐ Every 3–6 months ☐ Annually ☐ Once after deployment ☐ Unknown ☐ Different:	

Data and Storage Management

Questions	Answer Options	Score / Comment
Are data retention and deletion strategies defined?	☐ Yes ☐ No ☐ Partly	
Has data been classified (e.g., core vs. archival)?	☐ Yes ☐ No ☐ Partly	

Monitoring and Evaluation

Questions	Answer Options	Score / Comment
Is the model's energy consumption during use estimated or monitored?	☐ Yes ☐ No ☐ Partly	
Are energy monitoring strategies defined?	☐ Yes ☐ No ☐ Partly	
Are there agreements to periodically evaluate or update the sustainability strategy?	☐ Yes ☐ No	

Assessment and Action Points

Score: How many checkboxes are marked?

Warning signs: Are there many "no" or "unknown" answers?

Action Points:

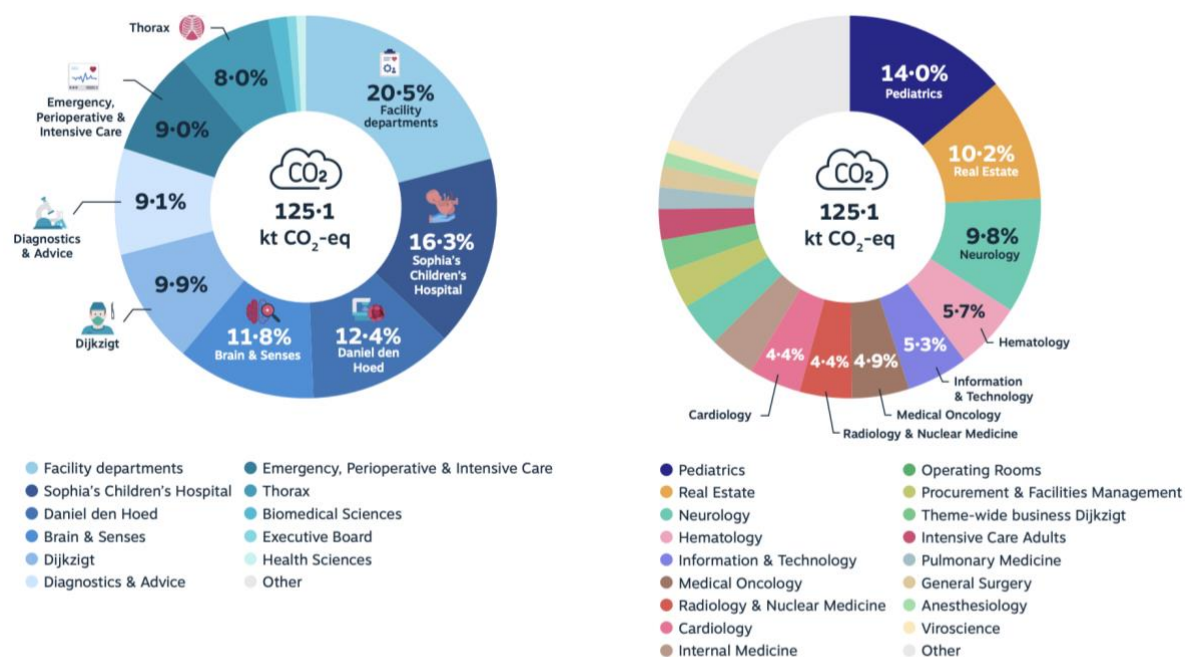
-
-
-

Figure 11 Sustainability Readiness Checklist for AI in Healthcare

5.6 Sustainability in Practice

While the proposed checklist offers an initial step towards embedding environmental considerations into decision-making for future AI practices, to fully understand and address the sustainability of AI in healthcare, specifically in SKZ, it is also important to examine current practices and determine action points. For this exploration it is important to note that as SKZ is part of Erasmus MC, they share an overarching policy and strategic vision. Considering Erasmus MC's strategy for artificial intelligence shows that the medical center emphasizes value creation for patients, healthcare professionals and society in general and therein makes no explicit reference to environmental sustainability (Slooff & Steketee, 2023). A policy document on the safe application of AI as a medical device, underscores the importance of ethical considerations in relation to AI, but does not include sustainability to this (Adriaanse et al., n.d.). The same applies for the data management plan of the hospital (Research Suite, Erasmus MC, 2023). Still, environmental considerations are made in an internal presentation on the ethics of AI at Erasmus MC, demonstrating an acknowledgement towards the ethical implications of AI. One of points referred to in the presentation slides is the need to *"promote responsive and sustainable AI"* (Schermer, n.d.). This phrase is copied from the World Health Organization's (2021) guidance on the ethical use of AI in healthcare. In this guidance sustainability, specifically in relation to minimizing the environmental impact and aligning AI development with broader climate goals, such as the UN Sustainable Development Goals (SDGs) is discussed. However, concrete elaboration on or implementation strategies for this principle is currently lacking within Erasmus MC.

Nonetheless, in 2021, Erasmus MC did conduct a study on the hospital's carbon footprint. According to this research, Erasmus MC emitted 125.1 kilotonnes of carbon dioxide equivalent in 2021 (Metabolic Consulting, 2021). 5.3% of this emission was attributed to the Information and Technology (IT) department, making IT the fifth most emitting department (figure 12). However, it is unclear how this percentage is distributed across different activities within the department and how much is specifically related to AI or data storage and processing practices. Furthermore, the hospital also distributed the CO₂ emissions to various themes, with the SKZ being labeled as one of them. SKZ was assigned a substantial 16.3% of the emissions from all hospital services and goods (figure 12).



Category 3.1 Goods and services GHG emissions, categorized into hospital themes (left) and hospital departments (right).

Figure 12 Contribution to carbon footprint of purchased goods and services on two organizational levels (Metabolic Consulting, 2021)

While this does imply a large amount of CO₂ emissions from IT activities, it is important to note that the study used a Life Cycle Impact Assessment (LCIA) method, which relies on physical quantities, combined with a spend-based approach, which estimates emissions by translating monetary expenditures (e.g., euros spent on goods and services) into emission (Metabolic Consulting, 2021). As written in the Erasmus MC report, spend-based estimations are considered less accurate. This method assumes a consistent relationship between cost and environmental impact, which is not the case. According to Heide & Gjerris (2024), spend-based assessments are not adequate enough as the cost of products rarely reflect the environmental harm they cause. Therefore, the authors emphasize the importance of a more value-informed approach, supporting the need for contextual and qualitative assessments, which can be conducted in the form of a qualitative lifecycle assessment.

5.7 Data Lifecycle

Stage 1: Data creation

Data within Erasmus MC is primarily created in the Hospital Information System (ZIS), of which the Electronic Patient Record (EPD) is a part. The EPD contains patient-specific information collected as part of standard care procedures. In a broader sense, ZIS also contains operational data about the hospital. This includes information about for example bed occupancy rates, surgery durations and scheduling. Both the EPD and ZIS are important

sources for AI development. When research, including research aimed towards AI development, is conducted, data gets transferred from these systems to a research data platform. In this platform models are developed.

An exploration on the process of data creation reveals that this process is not approached critically in terms of sustainability. As one respondent put it: *“I do not think we are very critical about what we store and what we do not”* (respondent 9). This is illustrated by the fact that there are reportedly *“over 50 ways of registering itch”* (respondent 9). This lack of critical reflection on data creation indicates that data creation is done without consideration for its consequences on the storage load of the created data. The reasoning behind this is related to the uncertainty of research. According to a researcher: *“You do not know in advance and that is a bit of the downside of research, what data you will need later”* (respondent 8). This illustrates that as (AI) research requires a lot of data (figure 9) and there is uncertainty about what data you need a tendency to create as much potentially valuable data as possible occurs, creating a tension between sustainability and the unpredictable nature of research. What makes opting for more sustainability and limiting research possibilities difficult in this tension is that: *“Virtually everything that is now considered the gold standard comes mainly from research. So I do not think you can say, ‘we will not do that anymore because it consumes too much energy’”* (respondent 8).

Nonetheless, though not from an environmental point, the data management plan of the hospital places great emphasis on the FAIR (findable, accessible, interoperable and reusable) principles for datasets (Research Suite, Erasmus MC, 2023). These principles aim to maximize the value of data by reducing data duplication and improving efficiency in data storage and reuse, mirroring the design requirement of data efficiency under the sustainability value (Figure 9). Although the FAIR principles apply to the creation and reuse of research datasets specifically, rather than raw data collection in general, they still shape how datasets which also take up storage are organized and used. Overall, due to clinical needs and the unpredictable and data demanding nature of research conducting sustainability efforts in raw data collection remains difficult. Still, the FAIR principles create opportunities for more sustainable research data(set) creation.

Stage 2: Data storage

At Erasmus MC, the created data is currently stored both on local servers and in the cloud. However, the majority of data is still stored on servers, as the transition to cloud storage is complex and ongoing. Nonetheless, for research data, the recommendation is to store it in a cloud-based research environment in which backups are made at least daily to safeguard data, adding to the overall storage demand (Research Suite, Erasmus MC, 2023). However, according to the IT expert, from a sustainability perspective, it is not necessarily the location or amount of storage that matters most, but rather the way in which the data is stored. As the IT expert said: *“We are primarily working on designing the architecture in such a smart way that the amount of data we store does not matter so much, instead it is about how and when you use that data and doing that smartly”* (respondent 9). This illustrates a shift in focus from data volume to data storage strategies, highlighting the importance of optimizing infrastructure and access.

An important concept in such storage strategies is the distinction between ‘warm’ and ‘cold’ data. Warm data is stored in a way that is immediately accessible, which requires high energy usage. Cold data, on the other hand, is stored further away from active data systems in a compressed format. Even though compressing data makes it less immediately accessible as it takes more time to retrieve, it also reduces the demanded storage space and energy consumption, contributing to sustainability. Still, a crucial consideration is that while storing data cold consumes less energy retrieving it does demand more energy. Therefore, it is useful to store data that is not used frequently this way. Currently, the exploration of smart storage strategies is driven by financial considerations, such as keeping storage costs manageable. However, they also carry potential environmental benefits as a smart infrastructure in which the energy demand is minimized indicates less environmental impact.

The challenge in designing such strategies arises from the fact that determining the way in which data gets stored is complex. Decisions about how to store data not only concerns the hospital itself but also alignment with different organizations. Aligning storage strategies across organizations is important to ensure interoperability and long-term usability. As one respondent noted:

“We can make a certain choice about how we store data. But if we then go to [another medical center] and say ‘Would you also store this data in the same way?’ so that we can

exchange data, then it all has to align. And not just in [the other medical center], but also in Norway and in the United States. So, you cannot just unilaterally decide, 'this is how I am going to store it.' It really requires collaboration on different levels to store data in a way that is future proof" (respondent 9).

This highlights the need for collaboration between organizations to develop sustainable and interoperable data infrastructures.

All things considered, for sustainability it is increasingly becoming more important how data is stored rather than how much or where. While large volumes of data are still needed for research, the environmental impact of increased data creation can be reduced by smarter storage designs. This makes the storage phase a crucial part of sustainability efforts. To increase sustainability in storage, it is therefore crucial to explore how infrastructure can be designed in a way that optimizes both accessibility and energy efficiency, while aligning with broader interoperability goals.

Stage 3: Data use

A considerable amount of data currently stored in the hospital is unstructured data, limiting the ability to use it. However, it is possible to structure components of this data to use for various purposes. For example, an unstructured consultation text may include information about a patient's blood pressure, which could potentially be extracted and used as structured data. While the hospital is increasingly becoming better at doing so, currently the structuring process is only partially possible, meaning that some data, despite its storage load and potential value, is unusable. Therefore, from an environmental perspective it is important to keep focusing on improving this process to avoid wasting storage space.

The data that can be used is mostly used for research, for example on creating AI models. The hospital provides a lot of data for AI development and as the data expert said, this happens often: *"Right now, as we always say at Erasmus MC, a thousand flowers bloom"* (respondent 9), once again affirming the presence of the AI hammer. However, besides AI solutions being explored a lot, another collectively acknowledged aspect of AI among stakeholders is that most of these research projects do not actually lead to tools being used in practice: *"But there are only a few that really make the translation from A to Z and actually make it to the clinic, because indeed during validation...the data quality is limited, the data you have for validation is limited"* (respondent 8). So, the use of data often results

in theoretical models that stay in the research part of the hospital, without actually creating practical value by contributing to clinical or administrative activities. To be able to use data more effectively and not waste energy, validation seems to be a recurring requirement, indicating that more data is needed in the future. Since Erasmus MC is a research hospital, it is important to think carefully about how that data will be created and stored in a way that is both useful and sustainable.

Stage 4: Data sharing

Sharing data is an important stage that can contribute to obtaining more sustainability by reducing waste through optimal resource use (figure 9). For instance, data on a rare disease can contribute to research only to a limited extent as it is not available in a sufficient volume to conduct validated research. As one respondent says: *“Look at brain tumors. We may only have twenty people a year who have such a tumor. Then there is not much point in doing research on twenty. Two hundred is actually very little”* (respondent 9). Sharing data among hospital increases the value of data, making it possible to conduct more validated research that would otherwise be limited due to data scarcity. This not only improves scientific outcomes but also contributes to sustainability by preventing redundant data collection and making better use of existing data.

At Erasmus MC, data sharing takes place both internally and externally. An important aspect of sharing and reusing data is that the informed consent given for this data needs to include a condition on sharing data, making it FAIR (Research Suite, Erasmus MC, 2023). If such a condition or question is missing from the informed consent form, the data is not FAIR and therefore not allowed to be shared for other research purposes.

To share data within the hospital, researchers can request access to datasets for their studies. Once the request is made a data steward evaluates if the requested data may be used for the proposed research. If approved, the steward settles the necessary paperwork and then ensures the data is delivered in the dedicated research environment. This process ensures that the data is shared in a secure and controlled way.

Externally, with for instance other hospitals, data is traditionally shared via a secure server that external researchers can log into. According to the data expert, this traditional method is still used in around 80% of the cases in which data is shared with parties outside the hospital. In addition to this method, a relatively newer approach called federated

learning is being explored. Within this method, for example, an AI model is shared with another hospital. This hospital sends back the output of that model after running it on their data, without sharing the patient data itself (Teo et al., 2024). As the IT expert said: *“In principle the data is of no use to you, only the results are of use to you”* (respondent 9). This process can then be repeated across multiple hospitals. The advantage of this method is that it increases the models’ validation, by running it through a higher volume and variety of data, without sharing sensitive or large datasets (ICT&health, 2023). Moreover, as the data expert explained: *“It is also a way to reduce the footprint”* (respondent 9). Sharing output would cost less energy and be less privacy sensitive than sharing large sets of actual data. This suggests that federated learning may contribute to a more sustainable approach to data driven research. However, despite different European initiatives’ focus on it, federated learning remains challenging to implement on a wide scale. According to the IT expert, this is because many different stakeholders are currently working on it independently, without a unified approach, making it inefficient. This lack of standardization and coordination slows down the potential benefits of federated learning and leads to findings being rediscovered.

Besides exploring federated learning, the hospital could also increase the value of data and reduce waste, by improving its capacity to make data available for sharing. This not only includes promoting FAIR principles to make data more reusable, but also investing in the infrastructure needed to actually share this reusable data. According to the expert: *“The more capacity we have to make data available, the more often people will use this”* (respondent 9). He adds the potential impact of improvements in infrastructure by adding: *“That could easily enable 40 percent more data deliveries”* (respondent 9). This indicates that investing in internal infrastructure and support for data availability could significantly increase the efficiency and sustainability of data sharing practices.

Stage 5: Data archiving

After a research project is completed, data is archived for traceability and potential reuse (Research Suite, Erasmus MC, 2023). Archiving is therefore a label for data that is no longer actively used within research but still needs to be preserved. Depending on the research type, documents can be archived from for at least 10 years to sometimes for at least 30 years, which creates a broad range of long-term storage obligations and environmental implications. Decisions on which data gets archived and for how long are made based on

various criteria, such as the cost of archiving, legal obligations, the type of data and its potential reuse value. While criteria such as the demanded storage capacity or the type of stored data are related to sustainability, the focus lies on the financial implications of these criteria. This means that sustainability is not explicitly integrated in this archiving considerations.

As discussed, when data is organized according to the FAIR principles this increases the likelihood that when it gets archived that data can be effectively reused in future studies (Research Suite, Erasmus MC, 2023). This way, FAIR adds more value to the archived datasets. Another environmental consideration is the used archiving formats. To ensure the durability of archived data, files are advised to be stored in both their original format and in additional preferred formats. While this increases storage volume, it also maximizes the possibilities for future reuse.

Furthermore, archived data is ideally not stored in the same location as the active project data, as this way of storing would be more expensive. Instead, the research suite advice to move the data to dedicated archive storage locations. Despite not explicitly being mentioned, cheaper storage indicates that the data is likely to be stored cold and more compressed. As the data expert indicates: *“Compressing data that is ultimately classified as cold... makes it significantly cheaper to store”* (respondent 9). While this type of data storage is presented as a financial recommendation to researchers, it also has environmental implications. Therefore, it is important raise awareness on critically assessing how archived data is assessed from an environmental perspective as well. For instance, awareness could be raised by including the environmental implications of storing data warm or retrieving cold stored data for reuse in the data management plan. This would allow researchers to make more sustainable decisions about their data archiving.

Stage 6: Data deletion

Another way to reduce the environmental impact of data is to delete it when it is no longer necessary or becomes redundant (figure 9). At Erasmus MC, raw source data does not get deleted for approximately 100 years: *“I believe we have to store patient data for 101 years, if I remember correctly. So that is very long. That also means we do not have much room to be critical about it”* (respondent 9). Because so far, no data has yet exceeded this period, no source data is being deleted. One exception to this is when a patient explicitly requests for

their data to be removed from the electronic patient record (EPD). In that case, the data is deleted from the EPD, which is linked with other systems in such a way that the deletion flushes through the whole system and is removed everywhere. Still, overall source data does not get deleted. Datasets used for research are archived for varying periods after the research is concluded. Once this period has passed, the research data is deleted. Nonetheless, these periods often last for at least 10 years and provide datasets that can be repurposed in different research.

Overall, due to constraints such as legal requirements, the traceability conditions in research and the value of having large data volumes, it remains difficult to apply more critical standards to data deletion. This shows that while data deletion could be a strategy to reduce storage demand and environmental footprint, in the context of healthcare, such measures are often limited by organizational, ethical and legal factors.

6. Discussion and Conclusion

This chapter reflects on the main findings of this research in relation to the central research question:

How can the Sophia Children's Hospital optimize AI-related decision-making and data practices to reduce the energy demand associated with AI without compromising patient care and operational efficiency?

The chapter begins with a conclusion that explicitly answers the research question and continues by discussing the findings of this study in relation to relevant literature and theoretical perspectives. After that the limitations of the study are addressed with corresponding suggestions for future research. The chapter closes with concrete recommendations on how the hospital can approach sustainable AI in the future.

6.1 Conclusion

This study explored how Sophia Children's Hospital can optimize its data storage and processing practices to balance sustainability with quality of care and operational efficiency. Through interviews with stakeholders, it became evident that the values of quality and efficiency are considered as important for data practices as well as for hospital practices overall. Although sustainability is still emerging as a priority, it is increasingly recognized as a factor to include in decision-making among multiple stakeholders. By including the design requirements, which are based on these values, into a cost-benefit analysis, an optimal balance can be created between energy usage, quality of care and operational efficiency. A value sensitive design that can be developed to make such an inclusion into the cost-benefit analysis is the Sustainability Readiness Checklist for AI in Healthcare (figure 11). The research also provided an assessment of current data storage processes at the hospital. By combining stakeholder interviews with a data lifecycle analysis, important sustainability challenges and opportunities were identified across the data lifecycle, particularly in the stages of data creation, storage and sharing. Although quantifying the energy demand of current data practices proved to be challenging as there is no standardized method and AI in healthcare is in its relatively early stages, the implications of AI practices on energy use can still be

assessed qualitatively as part of the readiness checklist. This qualitative approach can guide future decisions regarding AI. Different ways of data storage, particularly hot and cold data storage strategies, can be designed effectively, impacting these implications of data storage on sustainability.

6.2 Key Findings

The main findings of this research offer valuable insights into the practical challenges and potential strategies for promoting sustainable AI in healthcare, while also maintaining high quality of care and efficiency.

Currently, there is significantly growing attention for AI in healthcare including growing consideration for ethical concerns such as bias and privacy (Stahl et al., 2023). However, sustainability remains a relatively underexplored aspect in this discourse. This research addresses that gap by positioning sustainability as a core value, alongside and equal in importance to quality of care and operational efficiency. By adopting a design-oriented approach, the research defines corresponding norms and design requirements for all three values (figure 9) and structures them according to a bi-directional value-norm-requirement hierarchy model (Longo et al., 2020). These requirements can be integrated into AI-related design processes, offering an important contribution to more sustainable AI development. Besides they help understanding the complex value dynamics of AI in hospitals and therewith offer an approach to the wicked nature of normative complexity (Cribb et al., 2022; Head et al., 2022). Moreover, while value sensitive design approaches are recognized as a method in technology development, the structured use of a bi-directional value-norm-requirement model in hospital AI contexts, especially with the inclusion of sustainability as a value, is rare. This research helps filling that gap by applying the model in the context of Sophia Children's Hospital to guide more responsible and environmentally conscious AI practices.

Furthermore, current literature on environmental evaluations of AI systems emphasizes a quantitative approach, focusing on computational resources, like energy use and carbon emissions, required by AI models (Schwartz et al., 2019). However, the lack of a standard and reliable quantitative method (figure 10) challenges the efforts to measure the environmental impact of AI, particularly when attempting to make an a priori impact

estimation (Dodge et al., 2022). Building on the value-norm-requirement model, this study proposes a design concept (figure 11) for a qualitative assessment tool based on the design requirements for sustainability (figure 9). This design concept, proposing a checklist method, supports the integration of sustainability in the cost-benefit analysis of AI models in a way that reflects the practical value of sustainability. In doing so, the assessment concept supports a more context aware inclusion of sustainability into decision-making. This is particularly relevant because sustainability often involves trade-offs with other values and is therefore highly dependent on contextual factors (Cribb et al., 2022). The study therewith not only offers a method to assess AI sustainability qualitatively, but also a way to apply this method in a real-life, value-complex healthcare setting.

Besides the sustainable design requirements and design concept, this research proposes additional directions towards sustainable AI. It does so through a qualitative lifecycle assessment of data practices within Erasmus MC, of which Sophia Children's Hospital is a part, by identifying key areas for improvement. The most significant opportunities lie in the storage and sharing stages. For storage infrastructural strategies could reduce the energy demand of storage and reduce energy waste of storage by optimizing data usage. Optimizing sharing strategies could enable more efficient reuse of existing datasets. These insights support the energy reduction and waste minimization norms that correspond with the value of sustainability, as defined in the value-norm-requirement model (figure 9). Ultimately, the study offers actionable recommendations that support Sophia Children's Hospital in taking steps toward more sustainable AI but may also serve as a guiding example for other hospitals that aim to align their AI strategies with broader environmental goals.

6.3 Limitations

This study examined how sustainability and AI, as an emerging innovation, are connected within the context of healthcare. Therefore, the research was partly exploratory and aimed to map current practices, identify value tensions and propose a first step towards a responsible approach through a value-sensitive perspective. While it succeeded in developing a design concept based on design requirements the study also has some limitations that should be acknowledged.

Firstly, because AI is still relatively new in clinical settings and sustainable AI is an even more underexplored area, the study functions as a first exploration of sustainable AI. It aimed to investigate concerns, priorities and design requirements rather than develop a fully operational tool. Although the bi-directional value-norm-requirement hierarchy (figure 9) translated abstract values into design requirements and the Sustainability Readiness Checklist for AI in Healthcare (figure 11) offers a structured tool that can be used in practice, it remains an early-stage prototype concept. Within the Value Sensitive Design framework, design is an iterative process (Friedman, et al., 2008). In a full value sensitive process, the design would be evaluated and improved with the contribution of stakeholders. Due to time constraints and the scope of this research, it was not possible to fully develop the design concept into a prototype and subsequently share it with the stakeholders for feedback and validation. This limits the extent to which the checklist can be considered as feasible or effective in addressing sustainability of healthcare in a real hospital setting. Hence, the checklist should be further developed and evaluated in future research.

Secondly, the concept checklist currently focusses on sustainability, without the inclusion of quality or efficiency criteria. This choice was made due to the research's focus on sustainability and because the hospital did not request a method or design to incorporate these values into the cost-benefit analysis. If the hospital aims to explicitly incorporate criteria labeled under these values into the cost-benefit analysis, these could be integrated into the checklist in the future. The current checklist method allows for such expansion and the existing design requirements could serve as a foundation for doing so.

Thirdly, the research focused on the environmental impact of AI in terms of data and model use. It did not address hardware-related aspects of sustainability, such as electronic waste (e-waste) or energy consumption from physical infrastructure (Ueda et al., 2024). This choice was deliberate, as most AI models are not yet implemented in practice and end up as research. However, once operational use increases, future assessments should include the environmental costs of hardware.

Finally, generalizability is limited. Although two interviewees from another hospital were included, most of the study focused on Erasmus MC. Erasmus MC is an academic medical center with a strong focus on research. Consequently, findings and recommendations may be most applicable to similar academic or research-driven healthcare settings and may not translate to smaller hospitals or general care facilities as seamlessly.

For example, the emphasis on data sharing and dataset reuse for AI development is particularly relevant to academic hospitals due to their extensive focus on research activities. In contrast hospitals like Amphia, which do not conduct research on the same scale, primarily store data for medical purposes, making such reuse less of a priority. Nonetheless, situational adjustments could be made based on the hospital context and the suggestion to optimize storage architecture through practices like strategically distinguishing cold and warm data remains relevant across hospital types, as it addresses energy efficiency in data management, independent of research intensity.

6.4 Future Recommendations

Based on the value sensitive assessment of SKZ's AI and data practices several actionable starting points for sustainable AI implementation emerge that the hospital can build on in the future.

Further expansion of FAIR data creation: Ensuring data is Findable, Accessible, Interoperable and Reusable (FAIR), within the hospital's data infrastructure, not only improves the quality of data at the creation stage, but also increases its utility throughout the rest of the lifecycle. FAIR data allows more secure sharing, makes archived data reusable and helps ensuring that existing data is used more efficiently, reducing resource waste and the dependency on more data creation. FAIR data principles are already actively embedded in the hospital's data management plan. However, current decisions about data practices, such as storage duration and accessibility, are primarily guided by legal and financial considerations. To align FAIR data practices with sustainability, it is recommended to explicitly integrate environmental impact as an additional criterion in the data management plan. This could include, for example, adding sustainability-related guiding points to current archiving criteria, currently determined by among other things archiving costs.

Deeper involvement in federated learning initiatives: Federated learning offers a more sustainable approach to data sharing by enabling AI models to be validated across datasets from different organizations without transferring sensitive data. This contributes to improved model quality, better data protection and reduces energy usage associated with data transfers.

The European Commission has called for the creation of a pan-European ICU data infrastructure with the aim to improve collaboration between different European

institutions, enabling the development of better validated AI models. (Van Genderen et al., 2024). Erasmus MC is involved in this effort as part of an initiative aiming to establish a federated infrastructure for ICU data, with the European Society of Intensive Care Medicine as a key stakeholder. As part of this development, but also for other federated learning developments, it is recommended to, in addition to focusing on privacy protection and model validation objectives, explicitly include sustainability as a design criterion. Federated learning holds potential environmental benefits, such as reducing the need for large-scale data transfers, and as research indicates, minimizing CO2 emissions when the system is efficiently designed (Qiu et al., 2021). By incorporating sustainable design requirements to the federated infrastructure's design, Erasmus MC can contribute to both technological and ecological responsibility in healthcare.

Further development of data infrastructure and pipelining: Improving infrastructure is important for two reasons. First, to ensure that data is stored in a more energy-efficient and sustainable way. The hospital is shifting focus from controlling data quantity to storing and using data more intelligently, so that the volume matters less. It is recommended to formally develop guidelines on how data should be stored, including clear strategies for when to apply cold or warm storage strategies. This supports systematic sustainable infrastructure choices.

Second, to expand the hospital's capacity to make more data available for research and sharing, optimizing resource usage. According to the interviewed IT specialist, developing a self-service solution that prepares data in advance can enable researchers to access more usable data with less manual processing. This reduces inefficiencies and prevents data waste.

Further development and testing of the qualitative sustainability checklist: The concept prototype checklist developed in this study can be developed further and tested in future research projects, such as in a PhD trajectory or another thesis project. This would help evaluate its practical use and impact and embed sustainability considerations more systematically into AI decision-making processes.

Within this development, the checklist could be expanded in collaboration with policymakers and IT professionals within the hospital. Then, in collaboration with the AI accelerator team, the checklist could be tested through for example a pilot in which it gets included in the early development phases of a new AI model at Erasmus MC. After this

interviews or surveys could be conducted to assess whether the checklist supported value-based sustainable decision-making. The gathered insights would be valuable for refining and improving the checklist.

References

- Adriaanse, M., van der Geest, K., Greup, S., Groenendaal, L., Notenboom, S., Prummel, W., Sloof, M., & Steketee, R. (n.d.). *Beleid voor veilige toepassing van artificial intelligence als medische hulpmiddel in medisch specialistische zorg*. Erasmus MC.
- Ahmed, I., & Ishtiaq, S. (2021). Reliability and validity: Importance in Medical Research. *Journal of the Pakistan Medical Association*, 71(10), 2401–2406.
<https://doi.org/10.47391/JPMA.06-861>
- Armoogum, S., & Khonje, P. (2021). Healthcare data storage options using cloud. In A. Abraham, R. Aluvalu, M. A. Jabbar, & A. Madureira (Eds.), *The fusion of Internet of Things, artificial intelligence, and cloud computing in health care* (pp. 25–46). Springer International Publishing. https://doi.org/10.1007/978-3-030-75220-0_2
- Austin, C., & Kusumoto, F. (2016). The application of big data in medicine: Current implications and future directions. *Journal of Interventional Cardiac Electrophysiology*, 47(1), 51–59. <https://doi.org/10.1007/s10840-016-0104-y>
- Bans-Akutey, A., & Tiimub, B. M. (2021). Triangulation in research. *Academia Letters*, 2, 1-6.
<https://doi.org/10.20935/AL3392>
- Cribb, A., Entwistle, V., & Mitchell, P. (2022). Talking it better: Conversations and normative complexity in healthcare improvement. *Medical Humanities*, 48(1), 85–93.
<https://doi.org/10.1136/medhum-2020-012129>
- Desislavov, R., Martínez-Plumed, F., & Hernández-Orallo, J. (2023). Trends in AI inference energy consumption: Beyond the performance-vs-parameter laws of deep learning. *Sustainable Computing Informatics and Systems*, 38, 100857-.
<https://doi.org/10.1016/j.suscom.2023.100857>
- Dodge, J., Prewitt, T., Tachet des Combes, R., Odmark, E., Schwartz, R., Strubell, E., Luccioni, A. S., Smith, N. A., DeCario, N., & Buchanan, W. (2022). Measuring the carbon intensity of AI in cloud instances. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1877–1894). ACM.
<https://doi.org/10.1145/3531146.3533234>
- Donins, U., & Behmane, D. (2023). Challenges and solutions for artificial intelligence adoption in healthcare: A literature review. In L. C. Jain, R. J. Howlett, Y.-W. Chen, & S.

- Tanaka (Eds.), *Innovation in medicine and healthcare* (Vol. 357, pp. 53–62). Springer.
https://doi.org/10.1007/978-981-99-3311-2_6
- Erasmus MC. (2025). *Data board*. Agora. Intranet.
- Erasmus Research Development Office. (n.d.). *About us*. Erasmus SHTC. <https://www.shtc-erasmusmc.nl/about-us>
- Erasmus Research Development Office. (n.d.). *Strategy*. Erasmus SHTC. <https://www.shtc-erasmusmc.nl/strategy/>
- Friedman, B., Kahn, P. H., Jr., & Borning, A. (2008). Value sensitive design and information systems. In K. E. Himma & H. T. Tavani (Eds.), *The handbook of information and computer ethics* (pp. 69–101). John Wiley & Sons.
- Friedman, B., Kahn, P. H., Jr., & Borning, A. (2020). Value sensitive design and information systems. In K. Miller & M. Taddeo (Eds.), *The ethics of information technologies* (pp. 348–372). Routledge.
- Gierczyk, M., Gromkowska-Melosik, A., Scott, S. S., & Parker, C. (2024). The snowball sampling strategy in the field of social sciences: Contexts and considerations. *Przegląd Badań Edukacyjnych*, 2(43), 87–104. <https://doi.org/10.12775/pbe.2023.029>
- Greenhalgh, T., Engebretsen, E., Bal, R., & Kjellström, S. (2023). Toward a values-informed approach to complexity in health care: Hermeneutic review. *The Milbank Quarterly*, 101(3), 646–674. <https://doi.org/10.1111/1468-0009.12656>
- Hampson, I., & Junor, A. (2005). Invisible work, invisible skills: interactive customer service as articulation work. *New Technology, Work, and Employment*, 20(2), 166–181.
<https://doi.org/10.1111/j.1468-005X.2005.00151.x>
- Head, B. W. (2022). The rise of ‘wicked problems’: Uncertainty, complexity, and divergence. In *Wicked problems in public policy* (pp. xx-xx). Springer International Publishing.
- Heide, M., & Gjerris, M. (2024). Embedded but overlooked values: Ethical aspects of absolute environmental sustainability assessments. *Journal of Industrial Ecology*, 28(3), 386–396. <https://doi.org/10.1111/jiec.13472>
- ICT&health. (2023). *Federated learning heeft enorme impact op medisch-wetenschappelijk onderzoek*. ICT&health. <https://icthealth.nl/magazine/editie-01-2023/federated-learning-heeft-enorme-impact-op-medisch-wetenschappelijk-onderzoek>

- Jia, Z., Chen, J., Xu, X., Kheir, J., Hu, J., Xiao, H., Peng, S., Hu, X. S., Chen, D., & Shi, Y. (2023). The importance of resource awareness in artificial intelligence for healthcare. *Nature Machine Intelligence*, 5(7), 687–698. <https://doi.org/10.1038/s42256-023-00670-0>
- Katirai, A. (2024). The Environmental Costs of Artificial Intelligence for Healthcare. *Asian Bioethics Review*, 16(3), 527–538. <https://doi.org/10.1007/s41649-024-00295-4>
- Lannelongue, L., & Inouye, M. (2023). Carbon footprint estimation for computational research. *Nature Reviews Methods Primers*, 3(1), Article 9. <https://doi.org/10.1038/s43586-023-00202-5>
- Livebench.ai. (n.d.). *LiveBench AI*. Retrieved June 12, 2025, from <https://livebench.ai/#/>
- Longo, F., Padovano, A., & Umbrello, S. (2020). Value-oriented and ethical technology engineering in Industry 5.0: A human-centric perspective for the design of the factory of the future. *Applied Sciences*, 10(12), 4182. <https://doi.org/10.3390/app10124182>
- Lucivero, F. (2020). Big Data, Big Waste? A Reflection on the Environmental Sustainability of Big Data Initiatives. *Science and Engineering Ethics*, 26(2), 1009–1030. <https://doi.org/10.1007/s11948-019-00171-7>
- Masanet, E., Shehabi, A., Lei, N., Smith, S., & Koomey, J. (2020). Recalibrating global data center energy-use estimates. *Science (American Association for the Advancement of Science)*, 367(6481), 984–986. <https://doi.org/10.1126/science.aba3758>
- Metabolic Consulting. (2021). *Carbon footprint of Erasmus MC: Towards science-based targets – Landscape report* (ENG). Erasmus MC. <https://www.erasmusmc.nl/nl-nl/duurzaamheid/documenten-en-media>
- Mithun, A. M., Bakar, Z. A., & Yafooz, S. W. M. (2018). The realism of value sensitive design on user interface development. *2018 IEEE Conference on Open Systems (ICOS)*, 86–91. <https://doi.org/10.1109/ICOS.2018.8632820>
- Naffah, A., Pfeifer, V. A., & Mehl, M. R. (2025). Spoken language analysis in aging research: The validity of AI-generated speech-to-text using OpenAI's Whisper. *Gerontology (Basel)*, 1–12. <https://doi.org/10.1159/000545244>
- Porter, M. E. (2010). What is value in health care? *The New England Journal of Medicine*, 363(26), 2477–2481. <https://doi.org/10.1056/NEJMp1011024>
- Qiu, X., Parcollet, T., Fernandez-Marques, J., de Gusmao, P. P. B., Gao, Y., Beutel, D. J., Topal, T., Mathur, A., & Lane, N. D. (2021). A first look into the carbon footprint of federated learning. *arXiv*. <https://doi.org/10.48550/arxiv.2102.07627>

- Rahul, K., & Banyal, R. K. (2020). Data Life Cycle Management in Big Data Analytics. *Procedia Computer Science*, 173, 364–371. <https://doi.org/10.1016/j.procs.2020.06.042>
- Reid, R., et al. (2007). *Data lifecycles: Managing data for strategic advantage*. John Wiley & Sons.
- Research Suite, Erasmus MC. (2023). *Erasmus MC data management plan manual: Human-related research*. Erasmus MC.
- Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, 4(2), 155–169. <https://doi.org/10.1007/BF01405730>
- Sadollah, A., Nasir, M., & Geem, Z. W. (2020). Sustainability and optimization: From conceptual fundamentals to applications. *Sustainability*, 12(5), 2027. <https://doi.org/10.3390/su12052027>
- Samuel, G., & Lucassen, A. M. (2022). The environmental sustainability of data-driven health research: A scoping review. *Digital Health*, 8, 20552076221111297–20552076221111297. <https://doi.org/10.1177/20552076221111297>
- Schermer, M. (n.d.). *Ethiek van AI in het EMC* [PowerPoint slides]. Erasmus MC.
- Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2019). Green AI. *arXiv*. <https://doi.org/10.48550/arXiv.1907.10597>
- Slooff, M. J., & Steketee, R. M. E. (2023). *Visie en strategie artificial intelligence Erasmus MC*. Erasmus MC.
- Smith, E. M. (2009). Storage management: What radiologists need to know. *Applied Radiology* (1976), 38(5), 13–18. <https://doi.org/10.37549/AR1694>
- Song, C., Lin, X., & Shen, X. (2013). Secure and effective image storage for cloud-based e-healthcare systems. *2013 IEEE Global Communications Conference (GLOBECOM)*, 653–658. <https://doi.org/10.1109/GLOCOM.2013.6831146>
- Spiller, T. R., Ben-Zion, Z., Korem, N., Harpaz-Rotem, I., & Duek, O. (2023). *Efficient and accurate transcription in mental health research: A tutorial on using Whisper AI for sound file transcription* [Preprint]. OSF Preprints. <https://doi.org/10.31219/osf.io/9fue8>
- Stahl, B. C., Antoniou, J., Bhalla, N., Brooks, L., Jansen, P., Lindqvist, B., Kirichenko, A., Marchal, S., Rodrigues, R., Santiago, N., Warso, Z., & Wright, D. (2023). A systematic review of artificial intelligence impact assessments. *The Artificial Intelligence Review*, 56 (11), 12799–12831. <https://doi.org/10.1007/s10462-023-10420-8>

- Suha, S. A., & Sanam, T. F. (2023). Exploring dominant factors for ensuring the sustainability of utilizing artificial intelligence in healthcare decision-making: An emerging country context. *International Journal of Information Management Data Insights*, 3(1), 100170. <https://doi.org/10.1016/j.ijime.2023.100170>
- Teo, Z. L., Jin, L., Li, S., Miao, D., Zhang, X., Ng, W. Y., Tan, T. F., Lee, D. M., Chua, K. J., Heng, J., Liu, Y., Goh, R. S. M., & Ting, D. S. W. (2024). *Federated machine learning in healthcare: A systematic review on clinical applications and technical architecture*. *Cell Reports Medicine*, 5(2), 101419. <https://doi.org/10.1016/j.xcrm.2024.101419>
- Thurmond, V. A. (2001). The Point of Triangulation. *Journal of Nursing Scholarship*, 33(3), 253–258. <https://doi.org/10.1111/j.1547-5069.2001.00253.x>
- Tobin, G. A., & Begley, C. M. (2010). Triangulation as a method of inquiry. In T. Huber (Ed.), *Storied inquiries in international landscapes: An anthology of educational research* (pp. 423–428). Information Age Publishing.
- Ueda, D., Walston, S. L., Fujita, S., Fushimi, Y., Tsuboyama, T., Kamagata, K., Yamada, A., Yanagawa, M., Ito, R., Fujima, N., Kawamura, M., Nakaura, T., Matsui, Y., Tatsugami, F., Fujioka, T., Nozaki, T., Hirata, K., & Naganawa, S. (2024). Climate change and artificial intelligence in healthcare: Review and recommendations towards a sustainable future. *Diagnostic and Interventional Imaging*, 105(11), 453–459. <https://doi.org/10.1016/j.diii.2024.06.002>
- Van Aken, J. E., Berends, H., & van der Bij, H. (2007). Solution design. In *Problem solving in organizations: A methodological handbook for business students* (pp. 83–97). Cambridge University Press.
- Van Genderen, M. E., Cecconi, M., & Jung, C. (2024). Federated data access and federated learning: Improved data sharing, AI model development, and learning in intensive care. *Intensive Care Medicine*, 50(6), 974–977. <https://doi.org/10.1007/s00134-024-07408-5>
- VWS. (2023). *Integraal Zorgakkoord: “Samen werken aan gezonde zorg.”* Report | Rijksoverheid.nl. <https://www.rijksoverheid.nl/onderwerpen/kwaliteit-van-de-zorg/integraal-zorgakkoord#:~:text=In%20het%20Integraal%20Zorgakkoord%20staan,onder%20andere%20door%20de%20vergrijzing>
- Williams, M., & Moser, T. (2019). The art of coding and thematic exploration in qualitative research. *International Management Review*, 15(1), 45–55, 71–72.

<https://www.proquest.com/scholarly-journals/art-coding-thematic-exploration-qualitative/docview/2210886420/se-2>

World Health Organization. (2021). *Ethics and governance of artificial intelligence for health: WHO guidance*. World Health Organization.

<https://www.who.int/publications/i/item/9789240029200>

Zhang, Q., Meng, Z., Hong, X., Zhan, Y., Liu, J., Dong, J., Bai, T., Niu, J., & Deen, M. J. (2021). A survey on data center cooling systems: Technology, power consumption modeling and control strategy optimization. *Journal of Systems Architecture*, 119, 102253-.

<https://doi.org/10.1016/j.sysarc.2021.102253>

Appendices

Appendix A: Topic lists

Topic List Empirical Investigation

Dutch:

Introductie (5 min)

Introductie en doel van het interview

- Dank u wel voor uw tijd en deelname aan dit interview. Ik stel me nog een keer voor. Mijn naam is Nihal, en ik ben masterstudent Healthcare Management aan de Erasmus Universiteit in Rotterdam. Dit gesprek is onderdeel van mijn onderzoek naar hoe het Sophia Kinderziekenhuis dataopslag- en verwerkingspraktijken kan optimaliseren om het energieverbruik van AI en machine learning te verminderen, zonder dat dit ten koste gaat van patiëntenzorg en operationele efficiëntie. Ik wil in het komende uur graag uw perspectief horen over hoe deze aspecten in de praktijk samenkomen en welke uitdagingen of kansen u hierin ziet.

Vertrouwelijkheid en anonimiteit

- Dit interview wordt volledig vertrouwelijk behandeld. Voor een zorgvuldige verwerking van het gesprek zou ik het graag willen opnemen. Ik wil benadrukken dat alles wat u zegt anoniem blijft en veilig wordt bewaard. Gaat u hiermee akkoord? Uw deelname wordt zeer gewaardeerd, en als u op enig moment wilt stoppen of vragen heeft, dan kan dat natuurlijk altijd.

Introductie respondent

- Vraag naar hun functie, ervaring en dagelijkse verantwoordelijkheden.

Impact van AI (10 min)

- Wat is de impact van AI op uw werk?
- Welke voor- en nadelen ziet u?
- Op welke manier denkt u dat AI nog gebruik zou kunnen worden binnen uw werk?
- Heeft AI invloed op de besluitvorming binnen uw werkzaamheden?

Waarden (10 min)

- Hoe belangrijk vindt u het om verschillende waarden in balans te houden bij het gebruik van AI, en waarom?
- Hoe belangrijk vindt u het waarborgen van verschillende waarden en waarom?
 - duurzaamheid, operationele efficiëntie en patiëntenzorg en waarom?
- Hoe weegt u deze waarden tegen elkaar af?

Duurzaamheid (10 min)

- Ziet u mogelijkheden om datagebruik en data-opslag te optimaliseren?
- Hoe kan het energieverbruik van AI vermindert worden?
- Ziet u nog andere mogelijkheden om de impact van AI op energieverbruik, klimaat en milieu te verminderen?

- Wat zijn de kansen en uitdagingen hierin?
-

Operationele efficiëntie (10 min)

- Hoe kan het ziekenhuis ervoor zorgen dat binnen de context van AI de efficiënte gewaarborgd kan worden?
 - Hoe verhoudt dit zich tot mogelijke duurzaamheidsinspanningen?
 - Wat zijn de kansen en uitdagingen hierin?
-

Kwaliteit van zorg (10 min)

- Hoe zou het ervoor gezorgd kunnen worden dat de kwaliteit van zorg gewaarborgd blijft ?
 - Wat zijn de kansen en uitdagingen hierin?
 - Hoe verhoudt dit zich tot duurzaamheid en operationele efficiëntie?
-

Afsluiting

- Rond af
- Bedankt.
- Vraag of de respondent nog een opmerking heeft die hij/zij nog kwijt wilt of delen over het onderwerp.
- Vraag eventueel voor aanbeveling van andere mogelijke respondenten.

English:

Introduction (5 min)

Introduction and purpose of the interview

- Thank you for your time and participation in this interview. Let me briefly introduce myself again. My name is Nihal, and I am a master's student in Healthcare Management at Erasmus University Rotterdam. This interview is part of my research on how the Sophia Children's Hospital can optimize data storage and processing practices to reduce the energy consumption of AI and machine learning, without compromising patient care and operational efficiency. Over the next hour, I would like to hear your perspective on how these aspects come together in practice, and what challenges or opportunities you see.

Confidentiality and anonymity

- This interview will be treated with full confidentiality. To ensure an accurate analysis of our conversation, I would like to record the interview. I want to emphasize that everything you say will remain anonymous and be stored securely. Do you agree with this? Your participation is highly appreciated, and if at any point you wish to stop or have any questions, that is absolutely fine.

Introduction of the respondent

- Ask about their role, experience, and daily responsibilities.
-

Impact of AI (10 min)

- What is the impact of AI on your work?
 - What advantages and disadvantages do you see?
 - In what ways do you think AI could be used in your work in the future?
 - Does AI influence decision-making in your daily tasks?
-

Values (10 min)

- How important is it to you to balance different values when using AI, and why?
 - How important do you find safeguarding different values and why?
 - sustainability, operational efficiency, and patient care — and why?
 - How do you weigh these values against each other?
-

Sustainability (10 min)

- Do you see opportunities to optimize data usage and data storage?
 - How can the energy consumption of AI be reduced?
 - Are there other possibilities to reduce the environmental impact of AI in terms of energy use, climate, and the environment?
 - What opportunities and challenges do you see in this?
-

Operational Efficiency (10 min)

- How can the hospital ensure operational efficiency in the context of AI?
 - How does this relate to potential sustainability efforts?
 - What opportunities and challenges do you see in this?
-

Quality of Care (10 min)

- How can we ensure that the quality of care remains guaranteed?
 - What are the opportunities and challenges here?
 - How does this relate to sustainability and operational efficiency?
-

Closing

- Wrap up.
- Thank the respondent.
- Ask if they have any final thoughts or anything else they would like to share on the topic.
- Optionally ask for a recommendation of other potential respondents.

Topic List Technical Investigation

Dutch:

Lifecycle (IT Staff)

Introductie (5 min)

Introductie en doel van het interview

- Dank u wel voor uw tijd en deelname aan dit interview. Ik stel me nog een keer voor. Mijn naam is Nihal, en ik ben masterstudent Healthcare Management aan de Erasmus Universiteit in Rotterdam. Dit gesprek is onderdeel van mijn onderzoek naar hoe het Sophia Kinderziekenhuis dataopslag- en verwerkingspraktijken kan optimaliseren om het energieverbruik van AI en machine learning te verminderen, zonder dat dit ten koste gaat van patiëntenzorg en operationele efficiëntie. Ik wil in het komende uur graag uw perspectief horen over hoe deze aspecten in de praktijk samenkomen binnen de lifecycle van data en welke uitdagingen of kansen u hierin ziet.

Vertrouwelijkheid en anonimiteit

- Dit interview wordt volledig vertrouwelijk behandeld. Voor een zorgvuldige verwerking van het gesprek zou ik het graag willen opnemen. Ik wil benadrukken dat alles wat u zegt anoniem blijft en veilig wordt bewaard. Gaat u hiermee akkoord? Uw deelname wordt zeer gewaardeerd, en als u op enig moment wilt stoppen of vragen heeft, dan kan dat natuurlijk altijd.

Introductie respondent

- Vraag naar hun functie, ervaring en dagelijkse verantwoordelijkheden.

Creëren (Data Generatie) – 10 min

- Hoe wordt data gegenereerd binnen het ziekenhuis, vooral met betrekking tot AI-systemen?
- Wat voor type data wordt het meest gegenereerd en verzameld?
- Hoe zorgt het ziekenhuis ervoor dat alleen essentiële data wordt verzameld om duurzaamheid en operationele efficiëntie te ondersteunen?
- Zijn er uitdagingen in het toepassen van datareductieprincipes bij de data-generatie?
- Hoe ondersteunen of belemmeren de huidige technologieën de mogelijkheid van het ziekenhuis om onnodige data te creëren?
- Denkt u dat er manieren zijn om data op een energie-efficiëntere manier te creëren of bij te dragen aan de duurzaamheidsdoelen?

Opslaan (Dataopslag) – 10 min

- Hoe wordt data opgeslagen in het ziekenhuis, vooral met betrekking tot AI toepassingen?
- Welke systemen zijn er om ervoor te zorgen dat data efficiënt wordt opgeslagen zonder overmatig energieverbruik?
- Hoe zorgt het ziekenhuis ervoor dat onnodige of redundante data niet wordt opgeslagen?
- Hoe beïnvloedt datareductie het besluit over welke data wordt opgeslagen?

- Zijn er uitdagingen met interoperabiliteit tussen systemen bij het opslaan van data in verschillende afdelingen of eenheden?
- Hoe ondersteunt of belemmert de huidige opslaginfrastructuur het ziekenhuis in het behalen van duurzaamheids- en operationele efficiëntiedoelen?
- Hebben beveiligingsmaatregelen invloed op de efficiëntie of energiegebruik van dataopslagsystemen?

Gebruiken (Data Verwerking en AI Gebruik) – 10 min

- Hoe wordt de data gebruikt binnen het ziekenhuis, vooral door AI-systemen?
- Wat is de rol van AI in besluitvorming, patiëntenzorg en operationele processen?
- Hoe kan ervoor gezorgd worden dat AI en dataverwerking geoptimaliseerd zijn voor energie-efficiëntie, terwijl de zorgstandaarden behouden blijven?
- Zijn er uitdagingen in het balanceren van de behoefte van AI om grote hoeveelheden data te gebruiken met duurzaamheidsdoelen?
- Hoe ondersteunen de huidige technologieën, zoals AI en machine learning, de operationele efficiëntie met betrekking tot het gebruik van data?
- Zien jullie impact op de kwaliteit van de zorg wanneer AI-systemen gebruikt worden? Hoe wordt deze balans gewaarborgd?
- Hoe beïnvloeden de beveiligingsprotocollen het gebruik van AI in termen van operationele efficiëntie of energieverbruik?

Delen (Data Delen en Samenwerking) – 10 min

- Hoe wordt data gedeeld binnen het ziekenhuis, zowel intern als extern (bijv. met andere ziekenhuizen of derde partijen)?
- Hoe beïnvloeden interoperabiliteitsproblemen de mogelijkheid om data efficiënt te delen tussen systemen of afdelingen?
- Welke stappen worden genomen om ervoor te zorgen dat data veilig gedeeld wordt, terwijl energieverbruik in overweging wordt genomen?
- Zijn er conflicten tussen de behoefte aan naadloze datadeling en de duurzaamheidsdoelen van het ziekenhuis?
- Denkt u dat het verbeteren van interoperabiliteit kan helpen bij het verminderen van redundante data-opslag en -verwerking, en zo duurzaamheidsinspanningen ondersteunen?
- Hoe balanceren jullie de behoefte aan operationele efficiëntie bij het delen van data met de potentiële energiekosten die daarmee gepaard gaan?

Archiveren (Data Retentie en Opslag) – 10 min

- Hoe lang wordt data bewaard in de systemen van het ziekenhuis?
- Wat zijn de beleidregels voor het archiveren van data, en hoe wordt bepaald wanneer data niet meer nodig is?
- Hoe zorgt het ziekenhuis ervoor dat data op een energie-efficiënte manier wordt gearchiveerd?

- Zijn er systemen om data te identificeren en te verwijderen die redundant of niet langer noodzakelijk is, om onnodig energieverbruik te voorkomen?
- Hoe heeft dataarchivering invloed op datareductie en duurzaamheid?
- Belemmeren beveiligingsmaatregelen de efficiëntie van dataarchivering en energie-efficiënte opslag?

Vernietigen (Data Vernietigen) – 10 min

- Hoe gaat het ziekenhuis om met het vernietigen van data zodra het niet meer nodig is?
- Zijn er specifieke protocollen om ervoor te zorgen dat data op een veilige manier wordt vernietigd, zonder de duurzaamheidsdoelen in gevaar te brengen?
- Hoe zorg je ervoor dat data niet langer wordt bewaard dan nodig is, zowel voor naleving van regelgeving als om energieverbruik te minimaliseren?
- Welke uitdagingen komen er bij kijken om data veilig en energie-efficiënt te vernietigen?
- Hoe ondersteunt of belemmeren de protocollen voor datavernietiging de operationele efficiëntie en duurzaamheid van het ziekenhuis?
- Zijn er mogelijkheden om het vernietigingsproces efficiënter of milieuvriendelijker te maken?

Afsluiten

- Rond af
- Bedankt.
- Vraag of de respondent nog een opmerking heeft die hij/zij nog kwijt wilt of delen over het onderwerp.
- Vraag eventueel voor aanbeveling van andere mogelijke respondenten.

English:

Introduction (5 min)

Introduction and purpose of the interview

- Thank you for your time and participation in this interview. Let me briefly introduce myself again. My name is Nihal, and I am a master's student in Healthcare Management at Erasmus University Rotterdam. This conversation is part of my research on how the Sophia Children's Hospital can optimize data storage and processing practices to reduce the energy consumption of AI and machine learning, without compromising patient care and operational efficiency. In the next hour, I would like to hear your perspective on how these aspects come together in practice within the lifecycle of data, and what challenges or opportunities you see.

Confidentiality and anonymity

- This interview will be treated with full confidentiality. For accurate processing of the conversation, I would like to record it. I want to emphasize that everything you say will remain anonymous and be stored securely. Do you agree with this? Your participation is greatly appreciated, and you are free to stop or ask questions at any time.

Introduction of the respondent

- Ask about their role, experience, and daily responsibilities.

Creating (Data Generation) – 10 min

- How is data generated within the hospital, especially in relation to AI systems?
- What types of data are most commonly generated and collected?
- How does the hospital ensure that only essential data is collected to support sustainability and operational efficiency?
- Are there challenges in applying data minimization principles during data generation?
- How do current technologies support or hinder the hospital's ability to avoid unnecessary data creation?
- Do you think there are ways to generate data more energy-efficiently or contribute to sustainability goals?

Storing (Data Storage) – 10 min

- How is data stored in the hospital, particularly with regard to AI applications?
- What systems are in place to ensure that data is stored efficiently without excessive energy use?
- How does the hospital prevent unnecessary or redundant data from being stored?
- How does data minimization influence the decision about what data to store?
- Are there interoperability challenges between systems when storing data across departments or units?
- How do current storage infrastructures support or hinder the hospital in achieving its sustainability and operational efficiency goals?
- Do security measures affect the efficiency or energy use of data storage systems?

Using (Data Processing and AI Use) – 10 min

- How is data used within the hospital, especially by AI systems?
- What is the role of AI in decision-making, patient care, and operational processes?
- How can AI and data processing be optimized for energy efficiency while maintaining standards of care?
- Are there challenges in balancing the need for large data volumes in AI with sustainability goals?
- How do current technologies such as AI and machine learning support operational efficiency in data usage?
- Do you see any impact on the quality of care when AI systems are used? How is that balance ensured?
- How do security protocols influence the use of AI in terms of operational efficiency or energy consumption?

Sharing (Data Sharing and Collaboration) – 10 min

- How is data shared within the hospital, both internally and externally (e.g., with other hospitals or third parties)?
- How do interoperability issues affect the ability to share data efficiently between systems or departments?
- What steps are taken to ensure that data is shared securely while considering energy use?

- Are there conflicts between the need for seamless data sharing and the hospital's sustainability goals?
 - Do you think improving interoperability can help reduce redundant data storage and processing, thus supporting sustainability efforts?
 - How do you balance the need for operational efficiency in data sharing with the potential energy costs involved?
-

Archiving (Data Retention and Storage) – 10 min

- How long is data retained in the hospital's systems?
 - What are the policy rules for data archiving, and how is it determined when data is no longer needed?
 - How does the hospital ensure that data is archived in an energy-efficient way?
 - Are there systems to identify and delete redundant or no-longer-necessary data to avoid unnecessary energy consumption?
 - How does data archiving affect data minimization and sustainability?
 - Do security measures hinder the efficiency of data archiving and energy-efficient storage?
-

Destroying (Data Destruction) – 10 min

- How does the hospital handle the destruction of data once it is no longer needed?
 - Are there specific protocols to ensure data is destroyed securely without compromising sustainability goals?
 - How do you ensure that data is not retained longer than necessary, both for compliance and to minimize energy usage?
 - What challenges arise when trying to destroy data securely and in an energy-efficient way?
 - How do data destruction protocols support or hinder the hospital's operational efficiency and sustainability?
 - Are there opportunities to make the destruction process more efficient or environmentally friendly?
-

Closing

- Wrap up.
- Thank the respondent.
- Ask if they have any final thoughts or anything else they would like to share on the topic.
- Optionally ask for a recommendation of other potential respondents.

Appendix B: Code tree

