MASTER THESIS

AI use in healthcare: Exploring how healthcare AI impacts work practices and collaborative work among healthcare professionals

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Title	AI use in healthcare: Exploring how healthcare AI impacts work practices and collaborative work among healthcare professionals
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Abstract

The development and use of AI technologies in healthcare is rising rapidly, however the impacts of AI use on healthcare work remain unknown. This study investigated how the use of an AI-driven clinical decision support system for the diagnosis or treatment of patients shapes work practices of healthcare professionals in a hospital and how it impacts the collaborative work between them. A research model built the theoretical foundation by assuming that an AI technology's features offer shared, collective and individualized affordances to its users which allow for certain actions and activities in terms of AI usage that in turn influence work by shaping its characteristics, concerning *job autonomy and control*, *job feedback*, *skill variety and use*, *social and relational job elements* as well as *job demands*. An exploratory case study of a healthcare team in the neurology department of a Dutch hospital that implemented an AI system to aid the diagnosis of epilepsy was conducted, involving observation and interview sessions with team members. The raw qualitative data was transcribed and analysed in ATLAS.ti by using template analysis. The study results show that the AI system's development and initial use had tangible implications for the healthcare professionals' current work. In addition, AI use differed among groups and across groups of healthcare professionals in the team. Moreover, the new concept of predictable AI affordances was suggested, referring to affordances that AI users predict the AI to offer in the future based on knowing the AI system's purpose and future functionalities. This study adds new and supports existing considerations about AI perceptions and their implications for work. Further, it shows the value of an affordance perspective to AI developers and managers in hospitals for understanding and responding to how users perceive an AI technology.

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1. Introduction

As nowadays AI technologies are increasingly introduced in firms, it is expected that how work is structured and jobs are designed will change (Haenlein & Kaplan, 2019). Particularly the healthcare sector is predicted to be heavily affected by AI-enabled technologies (Davenport & Kalakota, 2019; Abdullah & Fakieh, 2020; Lebovitz et al., 2022). The most impactful AI systems today are based on machine learning (Shaw et al., 2019) which is for instance used to build classification models (Lebovitz et al., 2021) and clinical decision support systems (Raymond et al., 2022). Shaw et al. (2019) see the main future use of ML in decision support systems, which are meant to intelligently support clinical decision-making in diagnosing and treating patients (Lysaght, 2019; Reddy et al., 2019; Bhardwaj et al., 2017). In fact, diagnosis and treatment are considered key AI application areas (Sanders et al., 2019).

Many scholars are convinced that humans and automated machines will collaborate and work next to each other (Davenport & Kalakota, 2019; Jarrahi, 2018; Haenlein & Kaplan, 2019), impacting how tasks and jobs are set up, specifically affecting workers' job, or work, design in terms of autonomy and control, skill variety and use, job feedback, job demands as well as social and relational aspects (Parker & Grote, 2020). These effects of an AI-technology on work design are not fixed and rather determined by the way it is developed and deployed, for example to what extent a human-centered approach is taken in doing so, meaning that organizations can actively influence a technology's impact on work (Parker & Grote, 2020). Further, by taking over tasks, AI could ease the burden on healthcare professionals who face many challenges due to the pressuring factors of demographic change, shortages in workforce, increasing morbidity as well as requirements in administration and changes in demand and expectations for information technology (Reddy et al., 2019). Moreover, AI-based technologies can allow healthcare professionals to focus on the more difficult and meaningful tasks by executing simpler routine jobs (Parker & Grote, 2020; Beam & Kohane, 2016). Another viewpoint is that balancing augmentation and automation could allow humans and machines to each focus on the tasks that fit their abilities, by humans on the one hand offloading tasks which machines can fulfill better but on the other hand staying ahead of machines in the tasks they excel at (Raisch & Krakowski, 2020). Specifically, AI technologies could take over complex analytical tasks to improve human decision-making and humans could handle uncertain, equivocal aspects of the decision-making process, thus deploying both for their capabilities (Jarrahi, 2018). Also, AI can offer the benefit of delivering care in a more efficient and equitable manner (Ronquillo et al., 2021).

On the contrary, another scientific perspective entails that workers will lose skills for tasks they are not required to do anymore since these will have become automated, leading to the deskilling of workers and blurring the lines for their responsibilities in the workplace (Parasuraman & Manzey, 2010; Skitka et al., 2000). Even more radical, some healthcare professionals are said to face the threat of being replaced by AI due to the automation of jobs it enables (Reddy et al., 2019), for example radiologists due to scientific evidence that algorithms already perform better at diagnosing tumors (Davenport & Kalakota, 2019). However, many scholars do not predict this to happen and rather emphasize that AI will augment professionals' work (Davenport & Glover, 2018) and that more likely only some tasks will be replaced instead of whole jobs (Parker & Grote, 2020; Shneiderman, 2020). The work of professionals is deemed too complex and multifaceted for machines to simply replace them, for instance the work of radiologists exceeds analysing and interpreting images for diagnostic purposes (Davenport & Kalakota, 2019).

The use of AI systems will not only change work and work practices of individuals, but also collaborative work (Kaasinen et al., 2022; Lai et al., 2021), and teamwork between professionals from different disciplines (Parker & Grote, 2020; Pelikan et al., 2018). In general, collaboration in healthcare is key to delivering high-quality, safe and efficient patient care (Anderson et al., 2020; Vyt, 2008, Wei et al., 2019). Teamwork can be regarded as a type of collaboration (Eichbaum, 2018). Smart solutions based on AI are promising to physically and mentally take the load off of healthcare professionals as long as human-machine teamwork puts human workers in the loop, does not overwhelm them and grants that they keep doing meaningful work (Kaasinen et al., 2022). Working with AI, team members' roles and relationships will change as new tasks and skill requirements arise (Kaasinen et al., 2022).

Looking at what is already known about how the use of AI impacts work practices and collaborative work among healthcare professionals, several research gaps exist. Firstly, there is a lack of research on the real-life use of AI technologies in the work environment of healthcare professionals (Von Gerich et al., 2022; Seibert et al., 2021). Even though AI systems and their usefulness for aiding clinical decision-making are rather often subject of research (Knapič et al., 2021; Gonzalez-Smith et al., 2022), their actual impact on clinical practice remains largely unknown. Consequently, the implications for the nature and quality of work are underexplored (Lebovitz et al., 2022) which is problematic since the use of AI technologies determines their effectiveness and usefulness (Petitgand et al., 2020; Parker & Grote, 2020). Secondly, studies dealing with the human side of artificial intelligence use in healthcare are sparse. Rather, a substantial body of research exists on studying and testing the capabilities and application contexts of AI technologies (Wu et al., 2021; Aljaaf et al., 2015; Karhade et al., 2022). This reflects the technology-centric implementation of healthcare AI (Sujan et al., 2022).

Hence, this research aims at qualitatively exploring how the use of an AI-driven clinical decision-support system for supporting the diagnosis or treatment of patients shapes work practices and impacts collaborative work between healthcare professionals in hospitals. Thus, the following research question is derived:

How does the use of an AI-driven clinical decision support system for the diagnosis or treatment of patients shape work practices, and how does it impact the collaborative work between healthcare professionals in a hospital?

To answer this question, a single exploratory case study in the neurology department of a hospital is conducted involving observations of and interviews with healthcare professionals who work with an AI-driven clinical decision support system to support the analysis and interpretation of electroencephalograms for the diagnosis of epilepsy. To the best of the researcher's knowledge, the research question has been unexplored to date.

This study contributes to clinical practice in several ways. Gaining a better insight into the actual effects of AI on work in healthcare can aid in developing healthcare AI systems as well as in improving and adapting the technology to the users' needs, shifting the focus from the technology to human workers (Sujan et al., 2022). Ensuring a fit of the technology to healthcare professionals and their work is the only way to unburden rather than overwhelm them (Kaasinen et al., 2022) and to allow for its effective use (Parker & Grote, 2020). On a theoretical level, this research contributes to theory by supporting other research on technology affordances and by proposing an extension of affordance theory with the concept of predictable affordances. Further, it underpins established insights on the importance of AI perceptions for AI usage and shows how an AI system used in clinical practice actually impacts and is expected to impact the work of healthcare professionals.

In chapter 1, the theoretical framework is laid out whereby insights from work characteristics and the concepts of technology affordances and constraints are adopted and united, as outlined in chapter 2. In the subsequent chapter the methodology is outlined. In chapter 4, the study findings are set out and analysed. In chapter 5, the results are discussed, followed by elucidating the theoretical and practical implications, study limitations, recommendations for clinical practice as well as recommendations for future research.

2. Theoretical framework

2.1 Machine learning in healthcare AI

Artificial intelligence (AI) refers to building systems that think and learn like humans as well as to imitating human cognitive functions in machines for the purpose of solving real-world problems (Holzinger et al., 2019). It aims at modeling intelligent behavior in machines with minimal human influence (Hamet & Tremblay, 2017; McCarthy, 2004). Since recent years, AI technologies are becoming more and more important in healthcare for a variety of purposes (Lysaght et al., 2019). Relevant kinds of AI in healthcare include data analysis systems based on algorithms (Sanders et al., 2019), natural language processing for understanding and classifying clinical documentation and research, robotic process automation in administration, physical robots and expert systems (Davenport & Kalakota, 2019) as well as big data analytics and computer vision (Raymond et al., 2022). As Shaw et al. (2019) suggest, machine learning algorithms are the most impactful type of AI in the healthcare sector and beyond. This kind of AI is relevant to this study. ML is a broad technique that underlies many other AI methods such as natural language processing, which is based on the two ML techniques deep learning and neural networks, as well as prediction models (Davenport & Kalakota, 2019). Deep Learning (DL) itself relies on artificial neural networks (Janiesch et al., 2021). A major drawback of artificial neural networks is the difficult interpretation of their outputs, as the layers used to build them are not visible and the learning process of the model cannot be tracked by the user, making them a *black box* (Lourdusamy & Mattam, 2020). Figure 1 shows an example of an artificial neural network, as visualized by Lourdusamy and Mattam (2020). Machine learning is also applied in computer vision, for instance to detect and classify objects and to extract information from graphical material such as images (Khan & Al-Habsi, 2020). AI-driven software platforms and algorithms for predictive modeling purposes are developed and used as a base for a range of applications that are meant to support decision-making in clinical practice by aiding diagnosis or screening (Lysaght et al., 2019). A common use case of these algorithms is to let them sort through big sets of data coming from various sources, filter it, organize it and try to find patterns with the aim of carrying out a probabilistic analysis intended to inform healthcare professionals responsible for making the final decision, as Lysaght et al. (2019) explain. Thus, in machine learning a system learns from training data specific to a certain problem to automatically build analytical models (Janiesch et al., 2021).

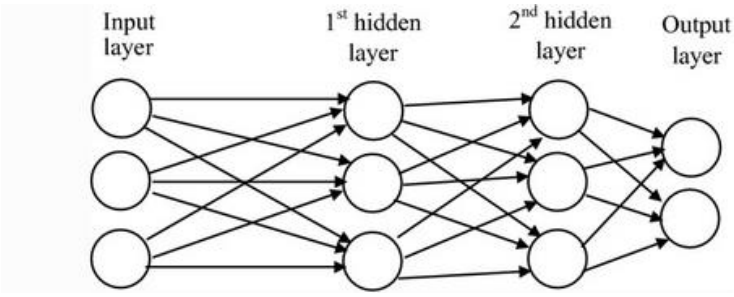

Figure 1: Example of an artificial neural network by Lourdusamy and Mattam (2020).

2.2 AI technologies as clinical decision support

As indicated in chapter 2.1, AI-driven decision support systems in clinical settings are already changing how healthcare practices are done by being implemented increasingly to support physicians in diagnosing patients, enriching work by allowing for more effective and accurate decisions which in turn ideally lowers costs, reduces human error and increases patient safety (Aljaaf et al., 2015). Apart from supporting diagnosis, these systems have been adopted to better detect and treat certain health conditions (Gonzalez-Smith et al., 2022). To create a guideline for the ideal choice of an AI technology within a clinical decision support system (DSS), Aljaaf et al. (2015) studied such *intelligent decision support systems (ICDSS)* which differ from regular DSS in the way that an intelligent module is applied to or even integrated into them and that use one AI technique or several AI techniques for solving complex problems (Maimon & Rokach, 2014). The same scholars differentiate between three types of ICDSS, portrayed in Figure 2 in a model directly adopted from Aljaaf et al. (2015): *knowledge-based ICDSS, machine learning ICDSS and hybrid ICDSS*. Machine learning based ICDSS are most commonly referred to as *non-knowledge based ICDSS* (Lourdusamy & Mattam, 2020). The firstly mentioned type is for example built on rule-based expert-systems (Aljaaf et al., 2015) which have been widely used in healthcare decision support applications but are gradually being replaced by more advanced algorithm-based machine learning approaches (Davenport & Kalakota, 2019). This ICDSS type is not considered in this research. Instead, the second and third type fit this research. Looking at machine learning ICDSS, generic algorithms and artificial neural networks have been successfully deployed for prediction and classification problems in

ICDSS and other applications (Kumar et al., 2007; Abbasi & Kashiyarndi, 2006; Moses et al., 2006; Aljaaf et al., 2015). In the nursing field, for instance, Raymond et al. (2022) found in their systematic review that all of the included studies looked at clinical decision support systems based on machine learning. Furthermore, the hybrid type of ICDSS, using both knowledge based and machine learning AI techniques, are also considered relevant since they are nowadays quite often used for prediction and diagnostic purposes (Aljaaf et al., 2015). A simplified graphical explanation of knowledge-based and non-knowledge based clinical decision support systems, created by Sutton et al. (2020), is presented in Appendix A to facilitate comprehension.

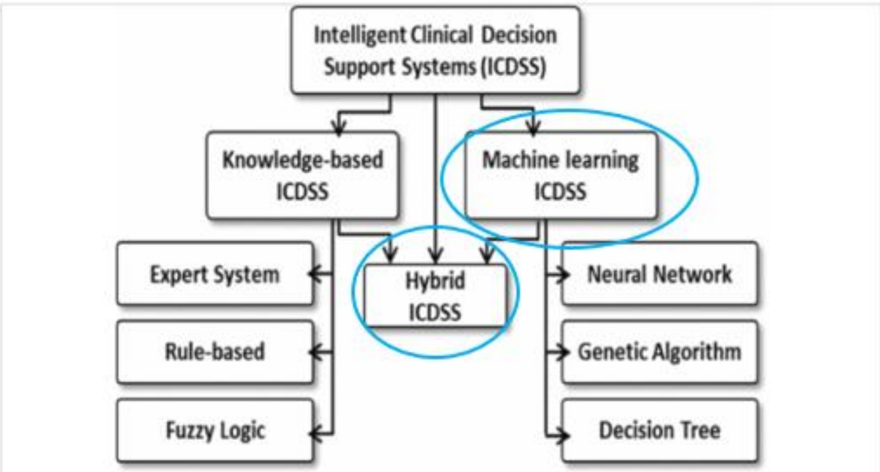

Figure 2: Three types of ICDSS by Aljaaf et al. (2015). Marked in blue are the types relevant to this study.

2.3 AI application areas in healthcare

AI technologies are developed and considered for implementation in healthcare practices associated with a variety of application areas. A number of scholars have presented an overview of these actual and potential applications (Davenport & Kalakota, 2019; Reddy et al., 2019; Sanders et al., 2019) who are now referred to in more detail. Davenport and Kalakota (2019) propose three key application categories of AI, namely *administrative activities*, *diagnosis and treatment recommendations* as well as *patient engagement and adherence*. Concerning administration, they see potential in the use of AI to enable more efficient work processes, for example for entering data, scheduling, ordering prescribed medication. triaging and clinical documentation (Sanders et al., 2019). Especially nurses who spent 25% of their work hours on administrative tasks could highly benefit from this (Berg, 2018). Looking at diagnosis and treatment, much focus in research and industry lies on AI development and use in precision medicine, particularly for cancer, and in generally providing more effective and accurate recommendations to healthcare professionals (Davenport & Kalakota, 2019). Sanders et al. (2019) also consider diagnosis and treatment as the main application areas next to administration. For example deep learning algorithms have shown to be highly useful for diagnostic purposes such as imaging, symptom analysis as well as for phenotyping, whereas personalized medicine, digital therapeutics, making treatment recommendations and assisting surgery are among promising AI applications (Sanders et al., 2019). However, application of AI in this area brings many ethical questions (Aronson & Rehm, 2015) and implementation problems in clinical practice (Davenport & Kalakota, 2019). Further, AI applications that invite patients for action and elicit it are developed to improve patient engagement in and adherence to their treatment (Davenport & Kalakota, 2019). Moreover, patient monitoring can be considered an AI application sub-category in diagnostics (Reddy et al., 2019). In light of this study's aim, the AI application category *diagnosis and treatment* as a crucial component of the healthcare delivery system will be considered, showing the most potential for transformation.

2.4 Impacts of AI use on healthcare work

Some scholars have developed categorisations of the impacts of AI use on work in and outside of healthcare (Makarius et al, 2020; Pee et al., 2018). Pee et al. (2018) refer to *augmentation* which they define as enhancing work by incorporating other experts' experiences in a system, thereby extending human cognition, whereas *automation* implies reducing the physical effort it takes to do human work. Additionally, two other forms of work transformation are identified, referring to *actuation* taking place when human workload is reduced by a system's autonomous work completion and to *assistance* which is applicable when the cognitive effort associated with doing human work is reduced (Pee et al., 2018). Somewhat differently, AI's impact on healthcare professionals' work can be described as a*ugmenting, replacing, splitting up* and *relieving* (Holdsworth & Zaghloul, 2022). Holdsworth and Zaghloul (2022) describe *augmenting* to happen when AI increases workers' productivity by enhancing their skills, *replacing* to be present when AI takes over a human job in its entirety, *splitting up* to occur when AI allows to split a task into several smaller tasks and takes over some of these and lastly, *relieving* is defined as AI carrying out simple everyday tasks and as a result granting healthcare workers more time for more vital tasks (Holdsworth & Zaghloul, 2022). In this research, the kind of impact, or even impacts, the AI system has on the work of healthcare professionals is, or are, determined by looking at work practices and collaborative work.

2.5 Work practices & collaborative work in healthcare

The concept of work practices can be defined as what actors in organizations do, referring to activities and actions individuals undertake in an organizational context (Geiger, 2009). On the one hand, work practices concern what is done routinely (Schmidt et al., 2007), hence typical workflows and tasks that are regularly done in the same way can be viewed as work practices. In a healthcare context, it can be argued that work practices encompass routinely done patient care processes and therefore include activities that are shared by healthcare professionals doing the same job (Bødker, 1991). On the other hand, non-routinized actions to meet individual patients' needs (Schmidt et al., 2007) and indirect patient care, such as doing administrative tasks, as well as employees' actions 'off-stage' in more informal spaces, such as partaking in work meetings, can be seen as integral to everyday work practices (Clancey, 2006). Further, work practices usually involve the use of technologies and other artifacts (Schmidt et al., 2007). Healthcare professionals are defined in this study based on the differentiation offered by Mickan et al. (2010) between unregulated and regulated workers in healthcare, with 'unregulated workers' referring to groups such as community workers, health system planners and healthcare assistants and 'regulated workers' to doctors, nurses, technicians and care workers. This research focuses on healthcare professionals in regulated professions, with the exception that assistants and residents are also considered in case they are involved in the AI-driven diagnosis or treatment of patients.

As indicated in the introduction, collaboration across professions and disciplines is essential for delivering high-quality, patient-centered care and to achieve positive outcomes on the provider and patient side (McLaney et al., 2022; Fewster-Thuente et al., 2008; Wei et al., 2019). Much research has already been conducted about interdisciplinary and interprofessional collaboration in healthcare (Reeves et al., 2017; Xiao, 2005; Vyt, 2008; Bossen & Foss, 2016). Interprofessional collaboration is defined as different professionals in healthcare coming together to use their disciplinary knowledge by offering it to health-impaired individuals in the form of services (Parse, 2014). Hence, collaborative work consists of a *"coming together of people at particular times and in particular places for an agreed set of tasks delivered through agreed roles and responsibilities, and that particular artefacts may serve as focal points for such complex, collaborative tasks"* (Greenhalgh, 2008, p. 1270). Essentially, collaborative work between healthcare professionals with different disciplinary backgrounds aims at providing the best possible care to patients and their families (Wei et al., 2019; Institute of Medicine, 2015; World Health Organization, 2010). Collaborative work presupposes that professionals voluntarily wish to unite for delivering patient care and that they at the same time want to stay independent and autonomous to a certain degree (D'Amour et al., 2008).

2.6 Theoretical perspectives on AI in work

2.6.1 Work characteristics

In light of human-AI collaboration in healthcare, individual work and teamwork are changing (Kaasinen et al., 2022). For this study, a work characteristics perspective is taken, predominantly based on Parker's and Grote's (2020) model which is heavily informed by the Job Characteristics Model developed by Hackman and Oldham (Torraco, 2005), to derive how the use of AI affects healthcare professionals' work. This is achieved by analysing how characteristics of their work, with work referring to their individual and collaborative work practices as described in chapters 2.5 and 2.5.1, are impacted by their AI usage. Prior research has shown the potential value of studying the influence of AI technologies on healthcare work from a job design perspective (Makarius et al., 2020; Tursunbayeva & Renkema, 2022). For example, a scoping review conducted by Tursunbayeva and Renkema (2022) revealed how the application of AI in healthcare affects healthcare professionals' jobs.

These job characteristics include *job autonomy and control, job feedback, skill variety and use*, *social and relational elements* as well as *job demands* which are essential to consider in designing work as they directly influence a number of job design outcomes, such as internal motivation, absenteeism, performance and turnover (van den Broeck & Parker, 2017; Torraco, 2005; Parker & Grote, 2020). The characteristics also impact how much responsibility workers have for their work outcomes (Hackman & Oldham, 1980). *Job autonomy and control* is defined as the discretion and freedom employees are granted to make their own decisions in their work, *job feedback* refers to whether employees receive clear and direct information about work outcomes and their effectiveness from the work itself and from others, *skill variety and use* is defined as the capacity to use a variety of skills during work, *social and relational elements* refer to support from and contact with others and lastly *job demands* can be captured as the organizational, physical, psychological or social job aspects that require mustering mental or physical effort for a considerable amount of time (Parker & Grote, 2020; Giles et al., 2017; Hackman et al., 1975; Hackman & Oldham, 1980). Additionally, *task identity* and *task significance* are considered a part of skill variety and use as they both refer to characteristics that make work meaningful (Hackman & Oldham, 1980; Parker & Grote, 2020), with the first concerning the capacity to complete a whole set of tasks rather than one component and the second denoting the significance, or importance, of the work for others (Parker & Grote, 2020; Hackman et al., 1975; Hackman & Oldham, 1980). Further, *role clarity* is investigated as a part of job feedback (Parker & Grote, 2020; van den Broek & Parker, 2017), which is particularly relevant to collaborative work (Greenhalgh, 2008; McLaney, 2022) as it refers to whether team members clearly understand their tasks and have clear information about the role they play in the team (Bray & Brawley, 2002; Parker & Grote, 2020).

Job autonomy in particular has been the focus of research and will become even more important as the roles of human workers and autonomous technologies will have to be redefined (Parker & Grote, 2020). Parker and Grote (2020) identify two types of job autonomy, with the first being decision-making autonomy over decisions concerning work processes and the second referring to timing and method autonomy in the sense of being able to decide when and where to work. Exemplary looking at nurses, Giles et al. (2017) argue that due to their complex work and varying requirements on the job, job autonomy allows them to make full use of their expertise, to solve problems effectively and increase the responsibility they feel for work outcomes.

2.6.2 Technology affordances and constraints

In the previous chapter, a perspective was presented on how to gain insights into the impact of healthcare professionals' AI usage on their work. Building on this, the following chapter presents a complementary theory that explains the way in which the AI usage itself comes about.

How an AI system shapes work practices and influences collaborative work can be traced back to certain actions or activities people perceive the technology to allow, or afford, which they act upon. Some scholars argue that objects afford certain actions through their material properties and that people perceive what an object can be used for before actually interacting with it (Gibson, 1986; Leonardi, 2011). Materiality can be defined as the intrinsic properties of a technological artifact that are fixed across time and place, for as long as they are not externally changed, coming about by a certain arrangement of its physical and/or digital materials into distinctive forms (Leonardi, 2012). As a consequence, in theory the characteristic features of a technology are available in the same way for every individual that uses it (Leonardi, 2012). However, the affordances a technology offers are not as they depend on each user's perceptions of the material properties (Leonardi, 2011). If a technology is not perceived to allow for a certain intentional action, this means that no affordances are recognized in it for this action (Markus & Sliver, 2008; Leonardi, 2011). However, an affordance can be viewed to exist independent of whether it is made use of or even noticed (Volkoff & Strong, 2013), but it is only actualized through a person that does so to reach a goal or fulfill an intention (Volkoff & Strong, 2013; Stoffregen, 2003). This firstly reveals the relational nature of affordances (Leonardi, 2011) as they are "a property [...] of the relationship between an object and an actor" (Volkoff & Strong, 2013, p. 822) which indicates that how exactly affordances are actualized can differ from person to person, however affordances still offer a general "potential for action" (Volkoff & Strong, 2013, p. 823). Secondly, based on their permanent existence, affordances can be described as potentials for goal-driven action at any point in time (Volkoff & Strong, 2013). Thus, in line with what is stated so far, affordances in this study are defined as *"[...] the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relation between an object (e.g., an IT artifact) and a goal-oriented actor or actors."* (Volkoff & Strong, 2013, p. 823). One object can be perceived by one person to offer several affordances and therefore lead to a number of different outcomes (Gibson, 1986; Leonardi, 2011, Volkoff & Strong, 2013). These direct outcomes are also actor-specific (Volkoff & Strong, 2013). In this research, affordances are actualized by healthcare professionals intentionally interacting with the material features of an ICDSS as the 'object' in question. This interaction leads to technology usage practices, in other words actualized affordances, which change the ways in which work is performed, thus shaping work practices and collaborative work.

Looking at a team level, according to Larson and DeChurch (2020) the use of a technology in a team gives rise to new work practices, since technology usage practices are developed when a team's needs meet material features of a technology that allow the team members to perform certain tasks. Additionally, where "heterogeneous actors co-exist [...]" (Islind et al., 2019, p. 435), which is the case in healthcare teams, different actors can perceive different affordances in the same technology (Islind et al., 2019; Leonardi, 2013). This means that the same features may be used differently by different people with divergent goals (Leonardi, 2013). Different usage practices can also occur if group members decide to use the technology's features differently to reach the same goals (Leonardi, 2013). In that regard, affordances can be further characterized based on the amount of people that recognize and actualize them in the same way, which is applied in this study. Analysing whether healthcare professionals use the technology's material features the same way or not gives insights into how similarly or differently the AI use affects their work practices and collaboration with each other. Also, it helps to see how effectively they coordinate work and perform at the individual and group level (Leonardi, 2013). Affordances that are shared by all members of a team can be overarchingly viewed as *shared affordances* meaning that all team members perceive them and use a technology's features similarly, whereas *collective affordances* are identified when a sub-group of members in a team uses the technology in different ways due to recognizing affordances the others do not see, allowing the whole team to accomplish something it otherwise could not (Leonardi, 2013). Moreover, *individualized affordances* are perceived and acted upon by a single person and are not shared with others in a workgroup, potentially allowing the person to be the only one being able to do a certain action (Leonardi, 2013).

Contrary to affording certain actions, a technology can also be perceived as constraining actions for realizing one's goals and if that is the case, changes to the technology itself need to be made to allow for a smooth integration into the workflow (Leonardi, 2011).

Overall, this study firstly tries to identify affordances and constraints that healthcare professionals perceive an intelligent decision support system to offer and entail, respectively. By doing so the affordances will be categorized into shared, collaborative or individualized affordances as outlined above. Secondly, the specific actions and activities in the form of AI usage practices that are afforded will be studied. The identified affordances essentially predict the ways in which and the purposes for which the technology is used and the constraints explain why all or some of its features might not be made use of. Additionally, changes that have happened and those that are desired for the AI system based on perceived constraints are considered as these hinder people from actions they want to do (Majchrzak & Markus, 2012). Moreover, these findings allow to make claims about the kind of general impact AI use has on the healthcare professionals' work, such as augmentation, assistance or replacement as described in chapter 2.4.

2.7 Research Model

In Figure 3, the research model is presented which unites the above presented theoretical perspectives and shows how they are applied to answer the research question. It is argued that making use of these two different theories allows for a well-rounded and deep exploration of how AI use impacts healthcare work, as they broaden the scope but at the same time are complementary lenses through which to study the research topic.

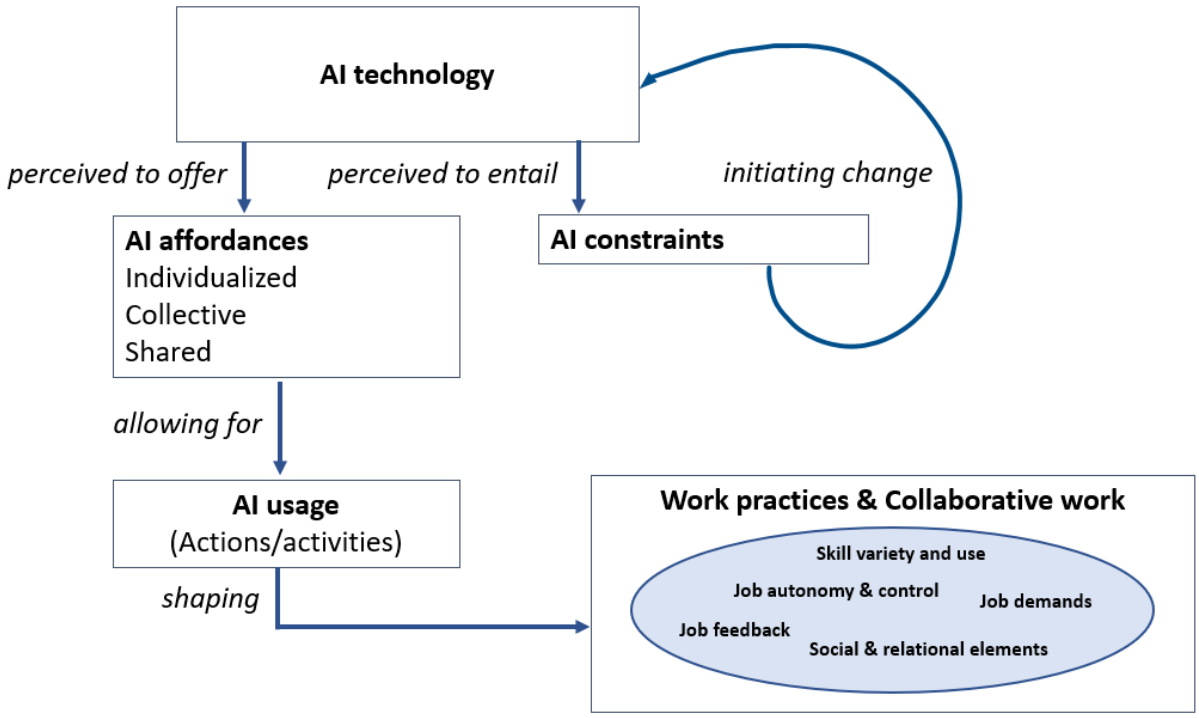

Figure 3: The two complementary theoretical perspectives united to approach the research question – work characteristics and technology (AI) affordances & constraints.

3. Methodology & Research context

3.1 Research approach & design

To give answers to the question of *how* the use of AI-driven clinical decision-support systems impact work practices of healthcare professionals in a hospital, an exploratory-descriptive research approach was chosen. This allows one to find first answers to questions on a topic that has not received much scholarly attention yet (Hunter et al., 2019) and to approach it in an open, flexible and pragmatic manner (Stebbins, 2001). Referring to the research design, a qualitative design was chosen because it seeks to unravel *how* things are happening by gathering rich data that can be used to derive in-depth inferences (Tetnowski & Damico, 2001). It also allows studying healthcare professionals in their work environment, enabling to gather data first-hand in an authentic setting and to pick up details and contextual aspects (Tetnowski & Damico, 2001).

As a qualitative research design, a case study was chosen which makes use of several data sources to approach 'how' questions (Baxter & Jack, 2008) and due to its open nature allows to somewhat redefine the boundaries of the case during data collection and analysis, if certain observations or findings guide into a particularly fruitful direction (Ylikoski & Zahle, 2019). Further, a single case study design was deemed suitable for this research since it aims at deriving insights on a phenomenon that has not been explored yet (Hunziker & Blankenagel, 2021; Boddy, 2016) and allows for making theoretical propositions (Ridder, 2017).

Additionally, comparable cases are rare since AI is sparsely implemented in healthcare so far (Gonzalez-Smith et al., 2022) and because the AI application areas of and AI techniques used in ICDSS vary greatly even in the one subfield of ML (Shaw et al., 2019; Aljaaf et al., 2015). Lastly, in this research an embedded case study design is applied to study two units of analysis, namely work practices and collaborative work, as described in the theoretical framework. Taking an embedded design allows to draw inferences for the case as a whole (Budiyanto & Prananto, 2019), thereby ultimately viewing the case from a holistic perspective (Rowley, 2002).

3.2 Data Collection

3.2.1 Sampling technique & sample size

Sampling in qualitative research is challenging since the ideal sampling strategy and sample size need to be carefully determined (Sandelowski, 1995; Marshall, 1996). In this study, purposive sampling of cases was applied for the selection of potential cases and subsequently the selection of the final case. Thus, cases were sampled for a single case study with the case being a team of healthcare professionals that works with an ICDSS in a clinical setting. Samples in qualitative research are mostly small considering that it usually deals with understanding a complex topic and exploring or describing it in detail (Marshall, 1996).

3.2.2 Case selection

The preliminary selection of potential cases as well as the final selection of one case were based on predefined criteria derived from the specifications of the research, thus promising to provide rich insights (Marshall, 1996). The following criteria were formulated:

- Use of an intelligent clinical decision support system (ICDSS), based on machine learning or a combination of machine learning and knowledge-based techniques
- Use of the ICDSS in real-life clinical practice
- Application of the ICDSS for diagnostic and/or treatment purposes in a hospital
- Healthcare professionals directly use the ICDSS

Potential cases were searched for using the search engine Google, focusing on AI technology that is already used in hospitals or other clinical care settings. Their websites and interesting linked sites were studied and the initial evaluation and selection of potential cases was done based on the selection criteria. Based on this, four healthcare teams were initially identified as potential subjects for the case study. As a next step, contact persons in charge of the work with the AI were approached via email or phone, describing the relevance of their case to this research and asking if they were interested to get in touch to explore the possibility of working together for the purpose of this research. A positive answer to this initial approach was received from two of the four contacts, whereupon a phone or video call was proposed to them in which the study specifications and actual fit of the case to the study would be discussed. The two contact persons from two different hospitals were willing to take part in such a session. Based on these sessions, it was ultimately assessed which case fit the study conditions and selection criteria best and whereupon one case was selected. The decisive factors were the AI technology specifications and application in real-life clinical practice. The selected case-study subject is a team in the neurology department of a large teaching hospital that works with an ICDSS for the diagnosis of epilepsy. This case is further introduced in chapter 3.6 and described in detail in the results section.

3.2.3 Data sources & collection techniques

This study applied the triangulation of data sources and data methods by making use of observation sessions while taking field notes, semi-structured interviews, meetings and analysis of online sources and documents. This overall approach to data collection has been used similarly in research on healthcare work practices (Igira, 2012; Rogers et al., 2004). The specifications for each data collection method are described in the following sub-chapters.

Prior to any data collection involving the participants, informed consent from all of them was confirmed prior to their study participation, following the approach by Wei et al. (2019). For each participant, the same informed consent procedure was followed. At the start of each observation and interview session, the researcher shortly briefed the participant by explaining that they will have to read an information sheet and fill out an informed consent form before they can participate in the study. These two documents are found in Appendices B and C, respectively. The purpose of doing so was explained and the room for questions was given. This procedure took about a minute whereupon the participant was handed the papers. Whenever needed, the researcher assisted the healthcare professional with filling out the consent form.

3.2.3.1 Observations

In this research, observation sessions were conducted by applying semi-structured shadowing which is a type of observation that requires to follow a person along while they are going about their daily work routine (Meunier & Vásquez, 2008), accompanying them to different locations in- and outside of the building (Sirris et al., 2022). This allowed to gain in-depth insights into the professionals' work while observing them and also communicating with them in the way that the researcher asked for explanation of a behaviour or task, particularly when it could not be simply observed (Sirris et al., 2022), or when the participant explained what they were doing on their own accord. In line with earlier research (Sirris et al., 2022), interviews were conducted after the shadowing sessions. In addition, the sessions were audio recorded when the professionals indicated to approve of that in the informed consent form which was the case with two participants.

Overall, four healthcare professionals using the AI-driven system were observed in one-on-one sessions with the researcher to gain insights into their individual and collaborative work practices and how those were impacted by the AI use. In Table 1, the professionals' functions and background information on their observation sessions are presented. As presented, two laboratory technicians in clinical neurophysiology, one clinical neurophysiologist and one resident in clinical neurophysiology were either observed while working with the AI system or during other parts of their work. The length of the observation session was agreed on with each participant individually, depending on what was feasible for them time-wise and what they felt comfortable with. Not all professionals participating in the study were observed, as they were given the option to choose between taking part in both, the observation and interview session, or only in an interview. Each participating professional was observed once, as it turned out that each session was insightful enough to understand and gain insights into their work and the ways in which the AI system is integrated into it.

During the observations, field notes were taken which was in the beginning informed by the structure shown in Appendix D. However, during the first session it soon became clear that it was too inconvenient and time-consuming to fill in the information that was observed or mentioned by the participant into the correct column on the right page. Additionally, organizing the data while collecting it appeared to be unnecessary as this could be done later and diverted the researcher's attention away from effectively observing the moment and capturing all that was considered noteworthy. Consequently, the researcher stopped adhering to the fixed structure during the first observation session and started to write impressions down in the order they appeared which significantly increased the researcher's productivity and attentiveness in the first and subsequent sessions.

Table 1: Specifications for the performed observation sessions

Observed healthcare professional	**Duration**	**Observed work**
Resident clinical neurophysiology (R1)	50 minutes	EEG review with AI system
Laboratory technician (LT1)	40 minutes	EEG review with AI system & demonstration of ambulatory EEG equipment
Laboratory technician (LT4)	45 minutes	Execution of a routine EEG session with patient preparation and discharge
Clinical neurophysiologist (N)	16 minutes	EEG review with AI system

3.2.3.2 Semi-structured interviews

Next to the observation sessions, semi-structured interviews were conducted to enrich the insights into the healthcare professionals' work and to refer back to observations made during the shadowing that required clarification or were worth further exploration. In total, eight interviews were carried out, again with different types of healthcare professionals who are involved in the AI-supported care in the team. Each interview took place in person in one of the offices at the neurology department and all of them were audio-recorded with the professionals' permission. The interview specifications are mentioned in Table 2. Further, the interview topics and questions were constructed based on the theories in the research model applied to answer the research question. To properly guide the interviews, an interview protocol was developed which is considered good practice for conducting semi-structured interviews (Harvey-Jordan & Long, 2001). This protocol was somewhat adapted for the interviews with the developers as some questions were not sensible to ask them. The standard version is presented in Appendix E.

Table 2: Specifications for the conducted interviews

Interviewee	**Duration**
Resident clinical neurophysiology (R1)	55 minutes
Resident clinical neurophysiology (R2)	34 minutes
Laboratory technician (LT1)	34 minutes
Technical physician (TP)	52 minutes
Laboratory technician (LT3)	58 minutes
Laboratory technician (LT2)	53 minutes
Clinical neurophysiologist (N)	36 minutes
Laboratory technician (LT4)	10 minutes

3.2.3.3 Informative meetings

Another source of valuable information were meetings held with key stakeholders in the team at the neurology department, referring to the healthcare professionals who are involved in the development of the AI system which are a technical physician and a clinical neurophysiologist. Two meetings took place, the first with the physician only and the second with the two professionals. The first meeting intended to gain a first understanding of the AI system and to see how it works in person which resulted in a 40 minutes long explanation and demonstration of the system. In Appendix F, a visual example is given of some learnings about the system. The second meeting took place to learn more about the AI system and the team's work on-site as well as to clarify the researcher's questions that arose during the first interviews and observations with their colleagues.

3.2.3.4 Other data sources

Other data sources made use of in this study were different kinds of online sources and documents, such as websites, news articles, scientific articles and documents used by the team in the neurology department. More specifically, these sources were used for the following purposes: Learning about epilepsy and epilepsy care, including EEGs and EEG software, obtaining background information on the team and its members as well as gaining an in-depth understanding of the purpose, functions as well as past and future development of the AI system used by the team. These sources are used in the results sections throughout chapter 4.1 until chapter 4.4.4.

3.3 Data analysis

3.3.1 Analysis strategy

To find patterns within the case (Ridder, 2017) and arrive at theoretical insights, the data from several sources was analyzed in a strategic manner. As a first step, the audio recorded data from the interviews and observation sessions was automatically transcribed in digital format by using the transcription software Amberscript. The field notes taken with pen and paper were organized. Based on these notes and the information that the researcher remembered from the data collection process, several visualizations were created in the form of mind maps and flow charts to gain an overview of important care processes and information about the AI system, as exemplary shown in Appendix G. In a next step, the raw data in the form of the transcripts was entered into the ATLAS.ti, a data analysis software for qualitative data to start systematic analysis.

To undertake the analysis process, an abductive approach was taken for a number of reasons. Firstly, when analysing the data it allowed to continuously intertwine theoretical insights with the data to derive findings, instead of having to decide between letting theory or data drive the sense-making process (Ahrens & Chapman, 2006). Thus, the interpretation of the data was done by looking at what it communicated, approaching answers to this by based on theory as defined in the theoretical framework as well as by learnings from the field, seeing how these could be united. Secondly, theory was used for different purposes in this study. In the beginning, existing theory was taken to create a strong theoretically informed basis to guide data analysis and to create a lens through which the research topic could be explored. For the interpretation of the findings at the end of the study, the initial theories as well as new literature were considered to draw inferences and interpret the findings. Searching for other studies and theoretical concepts which were not accounted for in the beginning was needed to explain and make sense of unexpected or new findings.

In line with this, in this study template analysis was applied. This is a type of thematic analysis which implies using hierarchical coding based on a coding template with main themes and sub-themes, offering structure on the one hand and a high degree of flexibility to adapt it according to themes that come up in the textual data (Brooks et al., 2015). Thereby, new codes were assigned as they emerged from the data, letting the data speak for itself to find meaning, allowing for it to reveal the most relevant information to answer the research question (Brooks et al., 2015). To generally prevent feeling lost in the data, the analysis was guided by three overarching questions, as formulated by Srivastava and Hopwood (2009) and depicted in Figure 4. An initial code book was developed with predefined main and sub-codes, as shown in Appendix H which was revised throughout data analysis and the final data structure is presented in Figure 5 in the subsequent chapter in which it is also explained how it was developed. This data structure was created based on the methodology used by Gioia et al. (2012) as well as by Ellmer and Reichel (2020). It allowed to structure the data visually and to show the connections between concepts, themes and dimensions. The difference to the approach by Gioia et al. (2012) is that the analysis process was throughout abductive and did not evolve from being inductive to abductive, however the data sense-making procedure itself of looking back and forth between relevant theory and emergent findings was similar.

Table 1. Questions that served as the framework for the data analysis
Q1: What are the data telling me? (Explicitly engaging with theoretical, subjective, ontological, epistemological, and field understandings)
Q2: What is it I want to know? (According to research objectives, questions, and theoretical points of interest)
Q3: What is the dialectical relationship between what the data are telling me and what I want to know? (Refining the focus and linking back to research questions)

Figure 4: Guiding questions for qualitative data analysis by Srivastava and Hopwood (2009).

3.3.2 Data structure

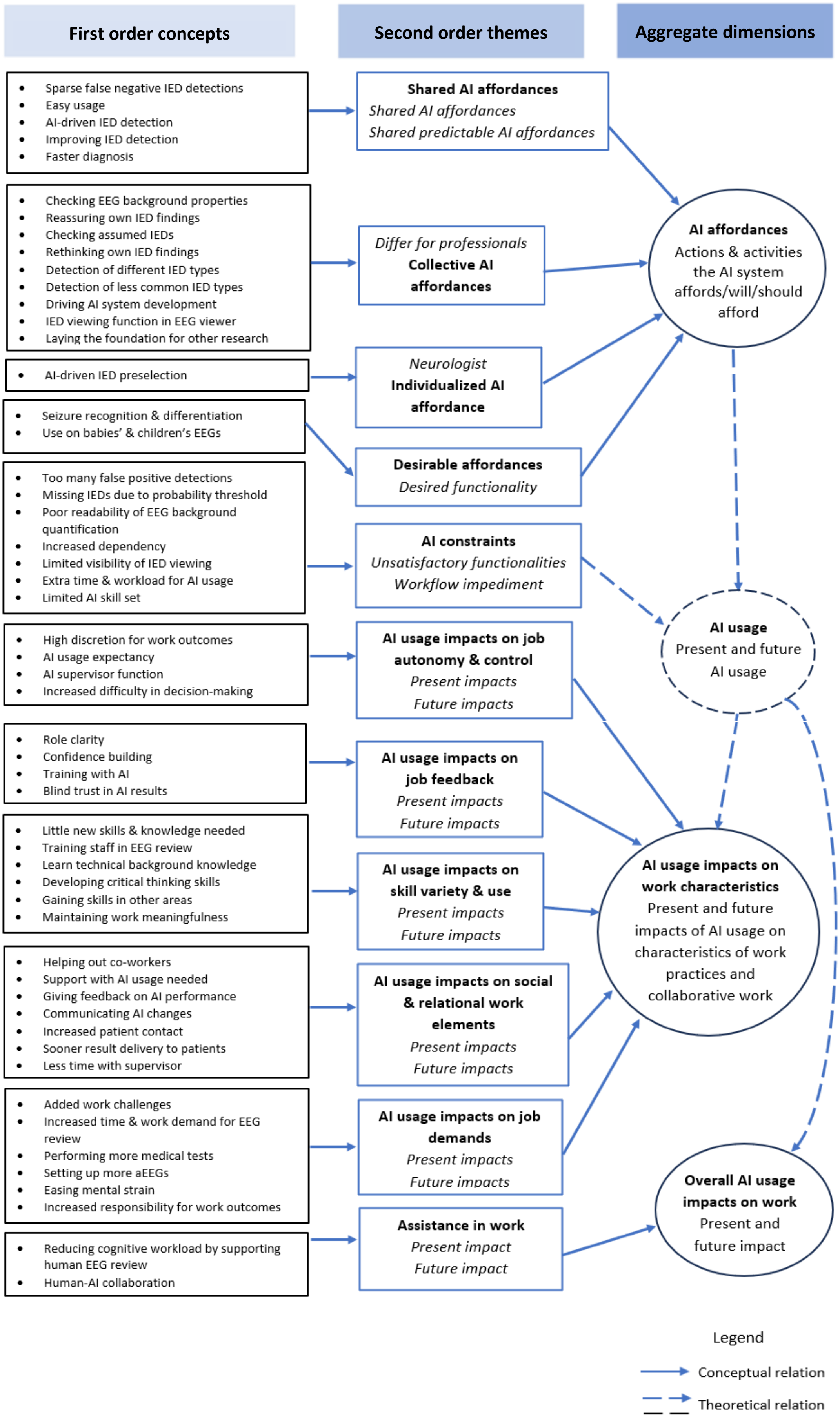

Figure 5: Resulting data structure, based on Gioia et al. (2012) and Ellmer & Reichel (2020).

As illustrated in Figure 5, a data structure resulted from the data analysis process which does not reflect the complete codebook as it focuses on showing the findings and relationships between them that relate to the concepts laid out in the theoretical framework. Nevertheless, also other data was coded such as the AI system's development specifications and descriptions of work practices.

Since template analysis was applied by developing a fine-grained codebook along the analysis process, the aggregate dimensions were included as the main codes a priori based on the theories that frame this research and guided the first round of analysis. In addition, some sub-codes, or second order themes, were pre-established based on the theory and were used to label data with. For example, 'AI affordances' was a predefined main code with the sub-codes 'shared affordances', 'collective affordances' and 'individualized affordances'. The first coding with this initial template was done with the first five transcripts which were four interviews and one observation session. Even though the codes were predefined at this stage, some main codes were rephrased or sub-codes changed based on the data found.

In a second round of coding, all transcribed interviews and observation sessions were analysed in more detail and the coding template was extended with more main and sub-codes by looking out for new open codes and emerging themes. Thereby, the coding template was "applied to further data, revised [and] refined" (Brooks et al., 2015, p. 203). This step led to the detection of many open codes which could be categorized into second order themes, in some cases third order themes, even fourth or fifth order themes, although not pictured in the data structure, as this was deemed best to capture the essence of the findings. During this stage in the analysis, the data structure was continuously revised as new insights were either directly derived from the data in the form of open codes or were gained by taking a step back and reflecting on what the data communicated by looking through the lens of theory in form of the predefined aggregate dimensions, allowing to generate new ideas (Chandra & Shang, 2019). For instance, by looking out for what could constitute one of the types of affordances or how the AI usage is impacting the professionals' work characteristics, it was inductively derived that some findings on shared affordances were predicted for the future. This new category of predictable affordances constitutes one of the main study findings. Overall, this coding round led to a fine-grained template which was subsequently used again on all of the data in the last round of coding.

In the third and last round of analysis, special attention was paid to whether new open codes and themes emerged that were not accounted for yet. This was not the case, however going through the data again initiated rephrasing a number of codes in the template as some constructs were perceived to be better understood now and therefore seen in a somewhat different light. After this recoding phase, the template was deemed finalized and data analysis was stopped.

3.4 Trustworthiness of the data

In qualitative research, establishing trust in the data is essential to instil confidence in readers about the researcher's reportings (Stahl & King, 2020). Therefore, measures were taken in this study to ensure this. Firstly, data source and method triangulation were applied to enhance credibility in the collected data (Baxter & Jack, 2008; Renz et al., 2018), thereby increasing the data's trustworthiness (Nolbeck, 2022). Secondly, as a method to ensure more credible findings (Connelly, 2016) and to guarantee that the participants were understood as they intended to be (Candela, 2019), member-checking was made use of by asking key stakeholders in the team, referring to the two professionals developing the AI system, for feedback on findings regarding the department, team, the epilepsy care process and descriptions of the AI system and its functionalities. Thereby, they were asked to give their honest feedback to whether the researcher's interpretations reflect their own perceptions of their work, allowing for an exchange about the findings and potential adaptations, making it a reflective practice (Candela, 2019). This helped to avoid an incorrect representation of the healthcare team and their complex work. Thirdly, to increase this study's quality, a code of conduct, found in Appendix I and entailing the principles followed by the researcher, as well as a confidentiality statement of patient information, as included in Appendix J were signed by the researcher. The participants were informed about these documents the researcher bound themselves to.

3.5 Ethical considerations

Before any data was collected, ethical assessment and approval was seeked from the Ethics Committee of the Behavioural, Management and Social Sciences Faculty of the University of Twente.

3.6 Research context

The research context, or case, which was selected to focus on in this study is situated in the Medisch Spectrum Twente (MST) which is a large top class clinical teaching hospital located in in the Netherlands with around 3500 employees (MST, 2023a). Further, it is a Dutch trauma centre and has outpatient clinics, a number of specialized centres and a wide range of departments at the main clinic in Enschede (MST, 2023a). The hospital closely collaborates with care partners in its region and its mission is to build the future of healthcare and to always offer added value to patients by applying a human approach combined with state-of-the-art and innovative technologies which are developed together with knowledge institutions such as universities and are implemented in clinical practice (MST, 2023a). The innovation of interest in this study is an AI system that is integrated in the workflow at the department of clinical neurophysiology to assist in the visual interpretation of electroencephalograms (EEGs). This analysis aims at detecting Interictal Epileptiform Discharges (IEDs) in EEG signals and is used to diagnose epilepsy (Lourenço et al., 2020). IEDs are patterns occurring in seizure-free EEGs signifying that the likelihood of epileptic seizures is increased (Lourenço et al., 2020; Da Silva et al., 2003; Pillai & Sperling, 2006; Smith, 2005). AI system users include clinical neurophysiologists, laboratory (lab) technicians, residents in clinical neurophysiology and technical physicians.

4. Results

4.1 The case context: Drawing the bigger picture

In the following sub-chapters, the neurology department and its team of healthcare professionals are introduced to set the stage for digging deeper into care processes and how they are affected by the AI system usage.

4.1.1 The neurology department

The neurology team in this case study is situated at the neurology department located on the second floor of the hospital where it conducts much of its daily work in a number of different rooms:

- Work/office rooms in which administrative work and other kinds of computer work such as reviewing EEGs is done. By using their identification card, the team members can access the computers. One of these rooms can be considered a shared workspace with several workstations.
- A common room allows the team members to gather for meetings and to have a break.
- Treatment rooms exists in which the equipment for routine and ambulatory EEGs is hooked up on and removed from the patient, where the routine EEGs are performed as well as rooms in which other types of medical tests are undertaken.

4.1.2 The team members and their work

In the following, an introduction to the daily tasks and activities of the different types of professionals in the healthcare team is given, focusing only on their work concerning epilepsy care. Their tasks that refer to other care processes can be viewed in Appendix K.

Laboratory technicians in clinical neurophysiology

The lab technicians in the team perform a variety of tasks and daily activities. They do not have a typical routine workday as their workload depends on the daily schedule they receive. In general, their main tasks encompass executing different kinds of medical tests with patients which concerns EEGs for diagnosing epilepsy. Besides preparing and performing these tests, the technicians do the administrative tasks in terms of handling patient data. Additionally, they review the medical test results, thereby doing the preparatory work for the neurophysiologists.

Clinical neurophysiologists

Looking at epilepsy care, the main responsibilities for the clinical neurophysiologists are to see, diagnose and treat ambulatory patients in the clinic as well as teaching and supervising neurology residents and technicians in training.

Residents in clinical neurophysiology
The neurology residents in the team are typically trained in the field for a minimum of one year. During this time, they rotate between different duties to learn about and gain clinical skills and experience in the diverse spectrum of tasks as future neurophysiologists. For epilepsy care, their work encompasses the analysis and interpretation of EEGs and subsequent discussions about findings with their supervisor as well as shadowing neurophysiologists during their work and taking part in theory training sessions.

Technical physicians
The technical physicians are oftentimes involved in direct clinical work as well as in scientific research activities. For instance, patients are seen for deep brain stimulation which serves to modulate neuronal activity, for example in patients with epilepsy and Parkinson's, selecting suitable candidates for this therapy and setting up the ideal stimulation settings for each patient. Considering scientific job elements, they can be involved in research projects or support students in their research.

4.2. Epilepsy and EEGs: Definitions and relevant background knowledge

4.2.1 What is epilepsy?

As one of the most commonly occurring serious brain disorders (Thijs et al., 2019; Hitiris et al., 2007), epilepsy is highly prevalent across populations around the world with more than 70 million people being affected (Thijs et al., 2019). It is a chronic condition and is "characterized by an enduring (i.e., persisting) predisposition to generate seizures, unprovoked by any immediate central nervous system insult, and by the neurobiologic, cognitive, psychological, and social consequences of seizure recurrences." (Beghi, 2019, p. 185). Epilepsy can affect men and women as well as people of all ages, however men are slightly higher at risk than women and those groups with the highest risk to develop the disorder are infants and the elderly (Beghi, 2019; Thijs et al., 2019).

Moreover, several risk factors for development of the disease are at play, with a genetic predisposition being a strong factor (Thijs et al., 2019). Other risk factors firstly include those directly causing brain damage and thereby triggering epilepsy such as head injuries, brain tumors, blood vessel malformations in the brain or a stroke, and secondly developmental disorders, dementia and certain infections can increase the risk for epilepsy (Mayo Clinic, 2023a). To make a precise diagnosis, epilepsy needs to be further classified on different levels, as presented in a framework in Appendix L.

Considering treatment, most patients respond well to anti-epileptic medication, however a third of cases are resistant to these drugs (Thijs et al., 2019; Hitiris et al., 2007). For some patients an alternative is neuromodulation therapy which in the widest sense consists of implanting a neurostimulator to electrically stimulate the brain directly or indirectly to adjust network activity (Ryvlin et al., 2021; Davis & Gaitanis, 2020; van Putten, 2023). If left untreated, the neurological disorder can lead to psycho-social dysfunctions, cognitive deterioration and heightened morbidity and mortality (Devinsky, 1999; Hitiris et al., 2007).

4.2.2 The EEG: An integral piece to the epilepsy diagnostics puzzle

Electroencephalograms, referred to as EEGs, are commonly used in clinical neurology to diagnose epilepsy as well as other medical conditions such as brain death, encephalopathy and dementia (Askamp & van Putten, 2014). Looking at epilepsy, EEGs are essential to capture epileptiform activity in the brain, more precisely epileptiform discharges (EDs) before (interictal), during (ictal) or after (postictal) epileptic seizures (Lourenço et al., 2021; Fisher et al., 2014). These discharges are important indicators of the disease which means that their presence supports an epilepsy diagnosis (Askamp & van Putten, 2014). Further, since seizures mostly occur infrequently and at unknown times, ictal EEGs are rare and therefore often times interictal EEGs are recorded for diagnostic purposes (Lourenço et al., 2021). Interictal epileptiform discharges (IEDs) mainly appear in an EEG as sharp waves and spikes (Lourenço et al., 2021).

The EEG signal itself is displayed as a graph on a computer screen (Institute for Quality and Efficiency in Healthcare [IQWiG], 2018). Precisely, "an EEG is a time-axis record of minute voltage changes measured through electrodes." (Sawa et al., 2021, p. 609f). An EEG allows to determine the type or types of seizures a patient suffers from as well as to rule out other medical conditions (Mayo Clinic, 2023a).

To record, view and analyse EEG data, EEG software is installed on computers at the neurology department that are used for these purposes. The classification of EEGs for the diagnosis of epilepsy is only one of the software's features, as it is also used for other clinical applications such as for seizure detection in patients with traumatic brain injury, to classify EEG patterns during coma as well as for assisting surgery on the carotid by offering real-time insights into the brain's electrical activity (Clinical Science Systems, n.d.). To give a visual impression of how the professionals can look at an EEG when analysing it, Figure 6 presents a snapshot of a recorded EEG signal as displayed in the EEG viewer used to analyse the EEGs. On the outer left side of the image the electrodes that measure the brainwaves are depicted with one pair of electrodes in each row constituting an EEG channel.

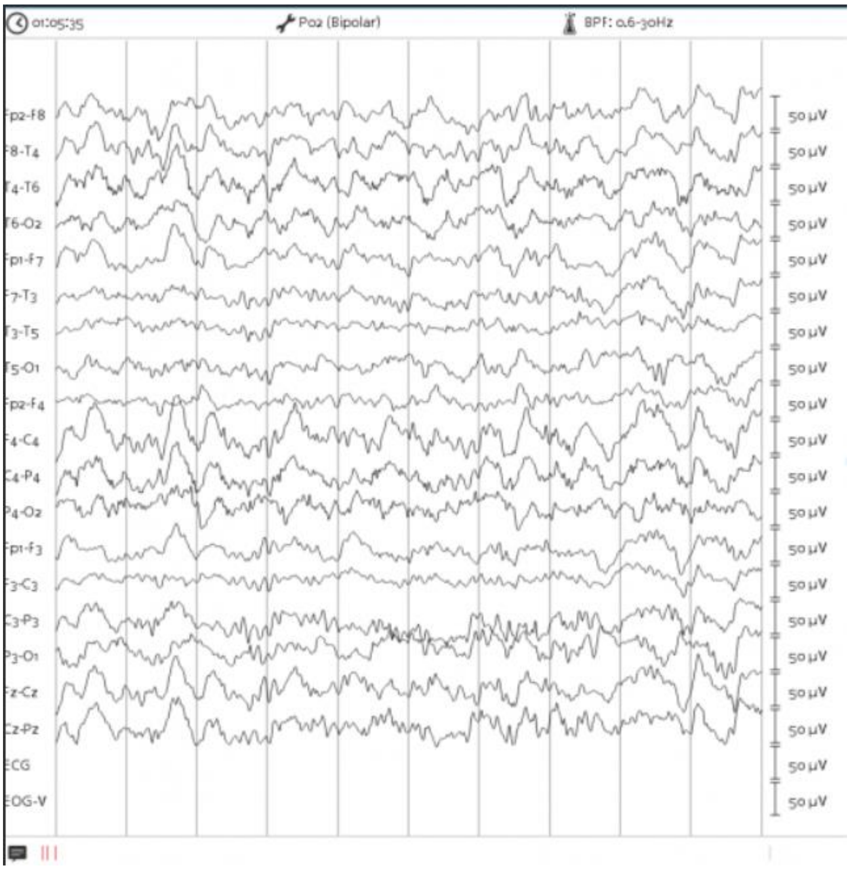

Figure 6: Snapshot of an EEG signal as shown in the EEG viewer (Clinical Science Systems, n.d.).

4.3 Epilepsy care at the neurology department

4.3.1 An overview: The typical epilepsy care pathway

Looking at epilepsy care in the neurology department of this case study, patients usually go through a certain process until they are either treated for epilepsy or are discharged with nothing abnormal detected.

Typically, the patient first presents themselves to their General Practitioner (GP) due to a first seizure episode of unknown cause. If the GP suspects epilepsy to possibly be the disorder behind the symptoms, they refer the patient to a neurophysiologist as the specialist who can do the further necessary examinations. During the patient's first appointment at the neurology department located in the outpatient clinic of the hospital, the specialist takes the patient's history and performs a neurological examination to gain an understanding of the patient's symptoms. On the basis of this, the decision for the execution of an EEG is made when the clinical picture remains unclear, however the specialist decides against an EEG if they assign the patient's problems another cause than a neurological condition such as epilepsy. Apart from an EEG, other medical tests to be performed in other departments might be prescribed to find the cause of the patient's seizures such as a CT scan, MRI, blood test or genetic testing, with the latter being relevant in case a genetic causal factor is suspected for the seizures (Mayo Clinic, 2023a). A CT scan or MRI allows to inspect the brain for potential structural causes of the seizures such as cysts or tumors (Mayo Clinic, 2023a).

If the neurophysiologist requests an EEG, the patient makes an appointment for the EEG session at the reception of the department. For first time patients, a routine EEG session is arranged. After the EEG has been recorded it is analysed and interpreted during a review process which is explained in chapter 4.3.3.1. If the test results turn out to be negative, meaning no abnormalities indicative of epilepsy are found, the specialist decides to at either at this point rule out an epilepsy diagnosis or to investigate further by requesting another type of EEG which is more likely to catch epileptiform activity, referring to the ambulatory EEG at home, as thoroughly presented in chapter 4.3.2.2. The decision to do this follow-up test is made when epilepsy is still suspected by the neurophysiologist even though the first test result was normal which is elaborated on in the last-mentioned chapter.

Hence, after having received the results of their routine EEG test, a patient might have to do the more laborious ambulatory EEG. This EEG is subsequently reviewed as well, as illustrated in chapter 4.3.3.2, and based on the results the neurophysiologist either makes an epilepsy diagnosis and therefore initiates adequate treatment or rules out the condition.

Further, as indicated this description reflects a typical process at the neurology department of interest for patients with suspected epilepsy. Some patients have different experiences, for example if they are first introduced to a neurophysiologist in a first aid setting.

4.3.2 In detail: Types of EEGs and associated work practices

Since the AI system at the neurology department is used in the context of epilepsy diagnostics, the different EEGs and associated work practices are described hereafter in regards to this medical condition. Different types of EEGs are conducted at the department in this case study which differ in usefulness, purpose, set-up and overall procedure for the patient. Apart from epilepsy, neurophysiologists can request an EEG for a patient in case of other diseases, such as metabolic disorders of the brain, dementia, postanoxic coma and to examine the brain development in children (MST, 2023b). Additionally, EEGs are measured at the hospital to support carotid artery operations (MST, 2023b). EEGs are usually recorded in the outpatient clinic, but are depending on their purpose also done in the operating room and nursing ward. If a patient is hospitalised as an emergency case, an EEG can also be conducted in the emergency department.

Two types of EEGs are typically done for the diagnosis of epilepsy at the neurological department which are standard, or routine, and ambulatory EEGs. The AI system of interest is used for both of these EEG types. A third type of EEG relevant in the context of epilepsy is the long-term EEG on the ICU, as it can be done for monitoring purposes, for instance in case of a status epilepticus which is a condition of a prolonged seizure or series of seizures between which the time interval is too short for the body to recover to its initial state (Deutsche Gesellschaft für Neurologie, 2012; Hufnagel, n.d.; Pockberger, 2002). However, since it is not typically used for the diagnosis of epilepsy and is therefore not affected by the AI system, it is not further considered.

4.3.2.1 Routine EEG

What, why and how?

The routine EEG is done with all first-time patients who have been referred to the hospital's neurology specialists by their GP due to neurological problems potentially indicative of epilepsy. Most of the time, patients come to their GP after having experienced a first seizure episode which gives rise to the suspicion of epileptic activity. Moreover, a routine EEG is also done if after some time a new one is needed for a patient to compare it with an older routine EEG of theirs and see whether the activity in the brain has changed, in other words whether deteriorations or improvements can be observed. For example, medical indications to do this comparison could be a re-emerged suspicion of epileptic seizures, following a prior EEG that was abnormal but did not show any epileptic activity, when a patient experiences reoccurring neurological problems that the specialists deem epileptic in nature. Another situation in which this kind of EEG recording takes place is when it turns out that the stroke-like symptoms of a patient who has been submitted to the hospital turn out to not be stroke induced, necessitating further expert investigation of the cause. Moreover, in some other cases patients wish to decrease their medication or stop it altogether which requires a new EEG to be done to see if there is still the same level of or any epileptiform activity, respectively, to be detected. Another point is that if a patient experiences problems due to epileptic activity particularly during sleep, a routine EEG is conducted in which the daytime sleep of a patient is recorded. This is achieved by prior to the session asking the patient to come in sleep deprived to be able to fall asleep during the EEG recording.

A routine EEG recording is performed by a laboratory technician specialized in clinical neurophysiology. It is performed at the outpatient clinic and usually takes 20 minutes to 30 minutes perform and taking the room and patient preparation before and the procedure after the actual recording into consideration, the whole session takes around 40 to 45 minutes. In essence, an electrode cap is set up on the patient's head by using the wet EEG system, as shown in Figure 7, and is connected to an amplifier that transforms and sends the EEG signal to a computer. The usual position of a patient during the EEG recording is depicted in Figure 8.

Figure 7: Exemplary depiction of the wet electrode system adopted from Nathan et al. (2013).

Figure 8: The position of a patient during a routine EEG session (MST, 2023b).

4.3.2.2 Ambulatory EEG

What, why and how?

The other type of EEG used to diagnose epilepsy is the *ambulatory EEG (aEEG)* which is a continuous recording of the brain activity for up to 24 hours at the patient's home. Recording brain activity for such a long time span implies that the sensitivity of the EEG is high, meaning that the likelihood to find abnormal events such as IEDs and even seizures is high. Further, this type of EEG is done for different reasons than the routine EEG. It is prescribed to a patient if the diagnosis after a routine EEG is not clear as there is uncertainty about whether the patient suffers from epilepsy or not. It can happen that a patient's routine EEG results are inconspicuous, however the neurophysiologist still suspects epilepsy to be the cause of the patient's problems. This is possible since the routine EEG has a low sensitivity due to the short time frame that it captures, meaning that the chance to catch epileptiform activity is quite low. Thus, it might simply be the case for some patients that during the 20 minutes of observed brain activity no events indicative of epilepsy occurred. For example, epilepsy symptoms oftentimes occur during sleep and an aEEG might be better able to capture the epileptic activity since the patient wears the EEG device during their natural sleeping hours. Such an aEEG can also be done when a patient is already in treatment and it needs to be checked whether they still experience epileptic discharges – in this case often at night. Also, an aEEG can be ordered by a neurophysiologist to after some time check whether a patient still experiences epileptic discharges during the day or night.

Considering the set-up, aEEGs need to be hooked up to the patient by one or two laboratory technicians at the outpatient clinic. This procedure takes about one to one and a half hours, depending on whether it's done by one or two specialists. The equipment differs from that of a routine EEG, as exemplary shown in Figure 9. Instead of getting an electrode cap to wear, single electrodes are glued to the patient's scalp between the hair. The exact points for the electrode placements on the head are measured, according to the 10-20 system explained in Appendix M, before attaching the electrodes to the head. These are then connected to a portable ambulatory EEG device, also referred to as EEG amplifier, which at all times records the EEG signal during day- and nighttime and stores the recording on an included SD card. This portable device can be worn around the waist or neck during the day and should be placed safely during sleep, for example above the head, as it needs to be worn without breaks until it will be removed at the outpatient clinic the next day.

During the EEG instalment procedure, patients are instructed to note down at what time certain activities take place, referring to when breakfast, lunch and dinner were eaten, when the patient went to bed and woke up as well as the time they watched TV, sat in front of the computer or walked longer distances. In addition, patients are asked to note down any seizure they have and its circumstances such as the duration, when it occurred, how they feel after the seizure and whether they know directly after where they are. These tasks are all handed to the patient on two papers for them to fill out.

Figure 9: Exemplary ambulatory EEG setup to be attached to the patient, showing the individual electrodes to be glued to the patient's head as well as the EEG amplifier device they are connected to and which records and stores the data (Micromed, 2023).

4.3.3 In detail: The EEG review process for an epilepsy diagnosis

To arrive at a diagnosis in the epilepsy care pathway, each patient's EEG has to be reviewed which encompasses a thorough analysis and interpretation. As described above, there are two types of EEGs performed at the neurology department when testing for epilepsy. In the following, the typical review process is described for both separately since the required workload as well as the type of specialist to review the EEG and their work practices differ. The following descriptions are based on the observation sessions the researcher conducted with some professionals in the team. Some visualisations based on the field notes taken and observations made during these sessions guided the following descriptions and are presented in Appendix N.

4.3.3.1 Routine EEG review

The routine EEG, as described in chapter 4.3.2.1 , is usually reviewed by the residents that are assigned to the neurology department together with a clinical neurophysiologist as their supervisor. First, the resident analyses and interprets an EEG on their own and writes their results down in a report. This initial analysis usually takes about 20 minutes, but can vary anywhere between 15 to 30 minutes, depending on the complexity and length of the EEG. Subsequent to this analysis, the findings and usually also the EEG recording itself are viewed and discussed between the resident and their supervisor. In times where no or not enough residents are working in the team, a neurophysiologist can take over the review task themselves. In the next sub-section, a typical routine EEG review process is described as observed by the researcher.

To start with the review process, the resident sits at an office desk facing two or three computer screens, depending on the room they are working from. Upon logging into the computer, first the doctor's note is checked to understand the patient history and medical indication. Questions such as '*what are the patient's problems?*' and '*why did they need an EEG?*' are thereby answered which helps the analyst to put the EEG into context. If the EEG is a follow-up EEG to compare with a prior one, the report for the prior EEG is checked to understand the signs of disease and have points of reference for what to pay special attention to during analysis.

Next, the resident opens the EEG recording in the EEG software, specifically in the EEG viewer, from a column of EEG data files listed as open for review. Moreover, a new report file is opened to note the analysis findings down for diagnostics and is placed on another computer screen to facilitate organised work. Having finished the preparation, the resident starts analysing the EEG page by page. During the analysis, the EEG is viewed from different perspectives by switching between EEG montages, allowing to look at different electrode arrangements to evaluate waves and other patterns from several perspectives, as each offers a different valuable insight into the electrical activity in the brain (Acharya & Acharya, 2019; Jadeja, 2021). Moreover, if considered helpful different filter settings offered by the EEG viewer are applied, for example to focus on certain frequencies one at a time, and quantitative analysis tools are used to summarise and plot EEG features which makes analysis and interpretation easier and more efficient.

First, usually the background pattern of the EEG is described in the report. The observed resident iteratively alternated between analysing the EEG and writing the report. Any notable event found was marked in the EEG recording, either by choosing the fitting description from a list of markers or by writing an annotation that shortly describes the observation. All marked and annotated observations are automatically listed and can be scrolled through to get back to a selected observation in the EEG by clicking on it. Observations that are looked out for during analysis are various and encompass the background pattern and its general properties, artifacts, eye movement and the heart's electrical activity, results from the tests run with patients during the EEG recording, any unclear occurrences, abnormal non-epileptiform activity, which can indicate other diseases than epilepsy with an example being narcolepsy, as well as of course epileptiform activity, such as epileptiform discharges and in some cases even seizures are captured. The detection of epileptiform activity is the mainstay for epilepsy diagnosis. When all findings have been noted, the resident writes the conclusion in their report. In a last step, the EEG recording with all the marked events as well as the report are saved and registered for discussion with the supervisor, as described in a subsection below.

Feedback & joint EEG review session

After the preliminary report has been written by a resident, the resident arranges a meeting with their supervisor to go over the EEG. During this session, they sit next to each other and the supervisor reads the resident's report and together they discuss the findings. At the same time, they look at the EEG recording and where necessary, the supervisor corrects what has been written and explains why the interpretation of certain observations needs improvement and which features in the EEG might need particular attention. Furthermore, sometimes group sessions with several residents are held. Overall, the final decision and responsibility for the diagnostic report lies with the supervising clinical neurophysiologist. These sessions offer valuable insights for the residents in their EEG review training process.

4.3.3.2 Ambulatory EEG review

Looking at ambulatory EEGs, their review procedure is undertaken by the lab technicians in the team at the neurology department. To analyse, interpret and note the findings down in a report, typically three to four hours are needed. This is attributable to the length of these EEG recordings and the fact that every page of the EEG needs to be checked which each displays 10 or 13 seconds of the recording, depending on the technician's preference. In a last step, a neurophysiologist is involved into the review as well by reviewing the technician's work. Hence, the technicians pre-process the aEEGs for the neurophysiologists. The specific work practices involved in the review of aEEGs are covered hereafter.

As learned from the interviews and observations with lab technicians at the department, the EEG review can start when patients come back into the outpatient clinic one day after their EEG was set up to wear at home. To access the recorded EEG data, the technician takes out the SD card from the EEG device and inserts it into an SD card reader connected to the computer in the technicians' main office room. The respective EEG file is opened in the EEG viewer. During the analysis itself, the observations and events that the technicians look out for in an EEG with suspicion of epileptiform activity largely overlap with those in the routine EEG analysis, as described in chapter 4.3.3.1. Also, the same kind of diagnostic report is written. However, there are a number of significant differences in their work practices, as observed and inquired by the researcher.

In general, no working time is scheduled for the lab technicians to do the EEG review, meaning that they have to do this work in-between their scheduled work activities whenever they have some spare time. This is attributable to a shortage in technicians which the neurology department is affected by, leading to the available technicians having to offset this lack of personnel. Hence it can take several days for one EEG review to be finished, dividing the EEG into sections to review. For instance, an hour during a workday to attend to the EEG review is already a lot and not the usual. Furthermore, it was notable that before and during the EEG analysis, technicians use the papers that the patients filled out during their EEG recording at home. This helps the technicians to pay special attention to specific times of the day or night as well as important events that the patients noted, for instance seizures. Particularly looking at the brain activity during sleep is essential when analysing an aEEG as most discharges occur during sleep. Moreover, a great number of artifacts occur in an aEEG during daytime, as patients are doing all kinds of activities and are seldomly in a relaxed state with their eyes closed. This adds complexity to the EEGs which is why a trained pair of eyes is needed for ambulatory EEG reviews. Therefore, only lab technicians with experience in analysing aEEGs do this kind of review.

Moreover, during the EEG review, the technicians prepare the initial diagnostic report, except for the conclusion, and mark all important events in the EEG, thereby automatically creating a list of these marked events. When they are finished, they save their work and put the papers with the patient's activities into one of the neurophysiologists' postbox. Thereafter, the neurophysiologist goes over the technician's list of marked events, their report as well as the forwarded papers and checks whether they agree with the results. Eventually the professional writes the conclusion in the report. The responsible technician is only reached out to in case something in their work is unclear to the neurophysiologist or needs to be discussed about the EEG.

4.4 AI in epilepsy care: The AI system in use at the neurology department

4.4.1 Purpose of the AI in clinical EEG classification

Processing EEG signals is essential in clinical neurology practice as well as for neurophysiological research and aims at classifying EEG signals as either pathological (epileptic), artifactual (activity not stemming from the brain) or physiological (healthy) (Nejedly et al., 2020). In the following, the purpose of and need for the AI system in the classification of EEGs for the diagnosis of epilepsy is described.

To date, the gold standard and binding procedure for reviewing EEGs is a visual analysis performed by specialists (Lourenço et al., 2020). Nevertheless, this method of EEG analysis has some major disadvantages, such as a long EEG review time, a long learning curve and the requirement for trained experts to perform the analysis (Lourenço et al., 2021; Tjepkema-Cloostermans et al., 2018). In fact, a lab technician needs around three to four hours for the analysis and interpretation of an ambulatory EEG recording from start to finish. In addition, “human error, subjectivity, intra and interobserver variability result in misdiagnosis rates up to 30%, leading to lack of treatment or prescription of medication with potentially harmful side effects” (Lodder et al., 2014a; Lodder et al., 2014b; Nowack, 1997, as cited in Lourenço et al., 2021, p. 1434). Another vital drawback of the visual analysis by the human eye is that ambulatory EEGs are not used on a widespread basis due to the time and resources that goes into their review, even though the diagnostic sensitivity for detecting IEDs is likely to improve with their use (Askamp & van Putten, 2014; Geut et al., 2017, as cited in Tjepkema-Cloostermans et al., 2018). As the trend is moving towards longer EEG recordings due to their added value and towards a higher sampling frequency, a mere visual review of the data is not sustainable anymore (Nejedly et al., 2020).

These circumstances have driven the development of computer-assisted detection of IEDs and interpretation of EEGs and efforts are made to integrate that into routine diagnostic processes (Lourenço et al., 2021; Tjepkema-Cloostermans et al., 2018). Deep learning promises to make similarly accurate detections of EDs as humans do (Tjepkema-Cloostermans et al., 2018) and it is likely that machine learning and deep learning algorithms will be integrated into the routine evaluation of EEGs, thereby reducing the resources and time spent to arrive at a diagnosis (Lourenço et al., 2020) and making results more objective as well as less variable (Lourenço et al., 2021). In Figure 10, the anticipated role of an AI-driven IED detection model in the typical epilepsy care pathway is illustrated.

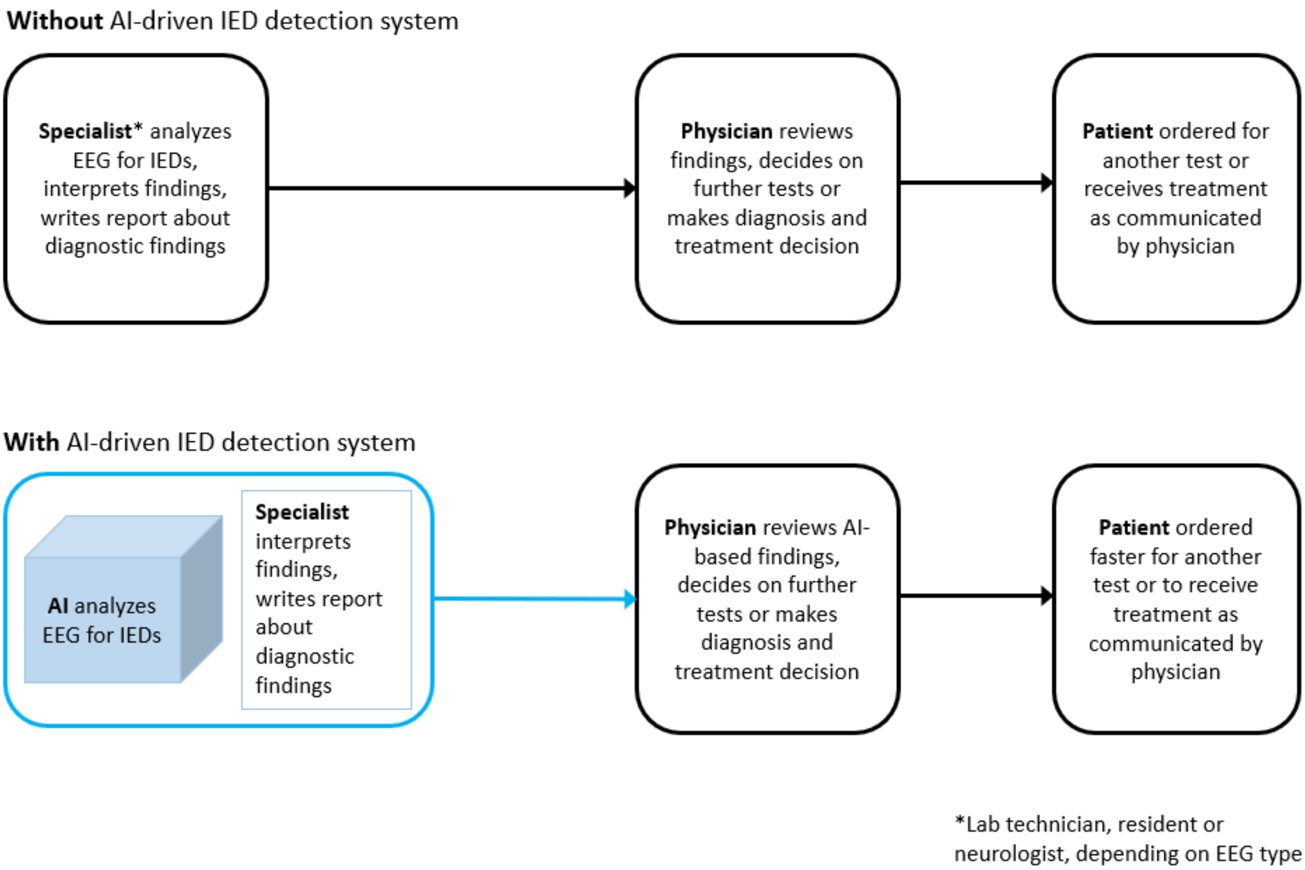

Figure 10: Simplified visual depiction of the typical epilepsy care pathway without and with an AI-driven IED detection system. This form of presentation is adopted from Pee et al. (2018).

4.4.2 The AI system development process

4.4.2.1 Pre-development

First looking at the pre-development stage of the AI-driven IED detection model, the technical physician reported that efforts to visually detect abnormalities in EEGs have always been made since the EEG technology was founded. To advance this, since the 20th century professionals have attempted to automate this work as it comes with a high visual burden. Different kinds of techniques have been developed over the last few years, yet visual assessment has been proven to be notably superior to them, expect for deep learning approaches as deep neural networks have shown to be able to accurately detect EDs in EEG recordings (Tjepkema-Cloostermans et al., 2018). This is depicted by one of the developers as follows:

> *"[…] There was also this, um, all the techniques in the past […], you try to build all templates of abnormalities and to try to fit those templates to these abnormalities. Or you should define some characters like, oh, it's really abnormal if the peak is like this and there's a slow wave afterwards. So […] then all these attempts were nice, but not not as good as human beings. So […] now with this AI developments […] we*

started doing that. But then with this technology and now we're finally in the end works." (TP)

4.4.2.2 Development

The first prototype of the AI-driven IED detection model was developed about four years ago, driven by the two developers in the team. Considering the current model version, a PhD student has been highly involved in building it and is currently further training it to advance its performance. The background quantification feature that is integrated into the AI system has been developed more than 15 years ago by the neurophysiologist in the developer duo. Moreover, an external ICT expert that the developers collaborate with for the technical matters has supported setting up and integrating the system into the department's infrastructure.

Considering how the novel IED detection model was trained so far, it was reported that its training has been performed completely in-house by the developers in the neurology team. More specifically, 250 EEGs, some aEEGs but mainly routine EEGs, were reviewed in detail by analysing and annotating every abnormal event in each EEG. The decision was made to use supervised learning for training the model which means that clearly labelled data was introduced to it, necessitating a rigorous EEG analysis to annotate each abnormality. One of the developers explained this procedure:

> *"[…] the point is, on one end, […] we can enter all of [the EEGs]. Yeah. Um, but those 250, we again looked in detail and again looked [N] annotated every abnormal event because I mean you can give an overall description of like 20 minutes and then you know, there's at least one abnormality somewhere in there, but then you don't know exactly where. So to train, we, we really, really annotated that, although there are also some techniques, […] now it's supervised learning. You can also do it unsupervised and then maybe the global […] description is good enough. […] But we really did a check."* (TP)

Furthermore, the IED detection model is still in ongoing development and the developers collaborate with other researchers, for example by sharing ideas on conferences, collaboratively publishing scientific papers and to compare the model with similar systems, thereby learning about its performance. Next to that, meetings are held on demand with others involved in the system's development, such as the PhD student and software developers of the EEG software in which the AI model has been integrated, as explained in chapter 4.4.4, to discuss questions, problems or new advances.

4.4.2.3 Implementation & clinical testing phase

Considering how the AI system is now implemented in the department, it took months and continuous work to get to this point. A little over a year ago, the current first AI system version was implemented in the neurology department. In the first months, it was only used by the two developers in the team since they wanted to be satisfied with it first and in addition, the system's accessibility was difficult initially, as it could only be run on a few computers. This required them to work on better integrating the application into the existing technical infrastructure. As of circa January 2023, a few other team members started to work with the system as well by accessing it on one of the few computers it could be used with. The two developers introduced the system to their colleagues in a session by explaining its functions and how to use it.

A few months later, multi-user access has been established which now allows to use the system from computers in any office at the neurology department. Specifically, the AI application is run on only one main computer in the MATLAB computing platform and can be accessed from other computers. When a user starts the system on another computer, it sends the EEG to this main computer for the EEG analysis to take place. When the analysis is completed, a report of the results is automatically sent back to the computer that issued the task. To send the EEG and subsequently let analysis take place, it is necessary that internet connectivity over the local area network is given.

Now that the AI system can be used by all team members who want to, it is actively used during work by two lab technicians for clinical neurophysiology that hook up and review ambulatory EEGs, by neurology residents working in the field of neurology for a few months as well as by clinical neurophysiologists/neurophysiologists. Particularly the neurophysiologist involved in the system's development has adopted it as an integral part of their work. This broader AI usage in the team marked the start of the AI system's validation phase which serves to answer the question of how the system is actually performing in clinical practice, considering that is has only been trained with retrospective EEG data so far:

> *"[…] so […] the first part is the validation. So how is it working now in the clinic? Because all these systems are trained on retrospective data, […] but that's different than, than to validate it in, in daily clinical use. That's what we do now. But then really as an add on. So first do the visual annotation, so visual description and then as an add on how well this performs and I think we will definitely learn from that."* (TP)

The lab technicians' contribution is vital in this stage as the developers rely on them to accumulate input about the system's performance that can be used to further train the model in a next step, as described in chapter 4.4.2.4. One of the developers stated this as follows:

> *"[…] there's a few lab technicians [that] review the ambulatory recordings and we are trying to ask them […] to use the AI system as well and compare their findings with the AI system. So that's basically a study in the background to look at time saving and also their experiences."* (N)

4.4.2.4 Future development

Speaking to the AI system's developers, it became clear that many research advances are planned to further develop the AI system, particularly the automatic IED detection.

Follow-up model training

One important point made is that the IED detection model will be further trained with more EEGs from this hospital and ideally also from other hospitals to improve its reliability:

> *"We are collecting more and more data. So we will do another training session for it in maybe in the next six months so provide it even with more EEGs. And we are also thinking of collecting data from other hospitals. So train it on data from other hospitals as well."* (N)

Looking at data from this hospital, to in the near future answer the question of how the AI system is actually performing in clinical practice, it is planned to take the observed EEGs from the current first clinical model validation phase and feeding its false negative and false positive detections in EEGs into the system, thereby advancing its performance as it improves based on learning from new EEG data. The technical physician explained this as follows:

> *"[…] well, one thing is to train it on more EEG data would be really nice if we now do this validation and the the events that it misses or that it makes a mistake. So false, negative or false positive that we can add this on the […] data to to get an update of the system."* (TP)

Model training by external experts

It was further stressed that training the model should not only be done by the developers themselves, but also by other experts from other clinical institutions. The rationale behind this is to incorporate other experts' knowledge in the system and to see how the model performs among different reviewers:

> *"And that's also something you should, you have also other reviewers training the data because now we're only learning our own. […] And it would be nice to have more experts."* (TP)

Model training with children's EEGs

Looking further ahead, at some point the system might be trained with EEG data from children and babies as it is only trained with EEGs from adults yet which would enhance the AI's applicability.

Broaden abnormality detection

Moreover, a possible future development is to let the system detect other abnormalities than epileptic discharges by feeding it with EEG data from epilepsy patients on the one hand and healthy individuals on the other, letting the system find features on its own that differ between the two types of EEGs. By learning on its own in this way, the model probably detects IEDs and additonally other features. These detections of abnormal brain activitiy could even be indicative of other conditions than epilepsy, hence broadening the model's usefulness in clinical practice.

Usability improvements

In terms of user-friendlieness, some possible improvements in the system's user interface, referring to the AI PDF report and AI integration in the commercial EEG software, were recognized by the developers. Firstly, it was mentioned that being able as a user to change the probability threshold that the system uses to identify discharges could be made possible in the future. Further, it was adressed to potentially build an additional system that can filter out the artifacts that are detected by the AI system to decrease the number of false positive detections which is considered a major drawback of the system at this point in time by certain team members. This means that changes in the AI that adresses two AI constraints professionals acknowledged, as explained in chapter 4.5.3, are already considered.

4.4.3 Underlying technology

The AI model to detect IEDs used at the neurology department is based on the deep learning technique due to its superiority to other methods in detecting IEDs, such as mimetic methods and morphological filtering (Lourenço et al., 2021). Talking about deep learning involves artificial neural networks which have many layers, in other words are networks with much depth (Lourenço et al., 2021). The main advantage of such a network is that it learns by example which works by introducing sufficient raw data for it to learn how to represent the features, or characteristics, found in the data and to then group new samples (Lourenço et al., 2021; Tjepkema-Cloostermans et al., 2018). This feature independence (Lourenço et al., 2021) allows to process the extensive amount of digitally available EEG signal data with such models (Tjepkema-Cloostermans et al., 2018), and promises that the model algorithm gathers more information from a signal since it can search for an unlimited number of characteristics instead of only focusing on recognizing a few pre-defined ones (Lourenço et al., 2021). The specific type of neural network underlying the AI system is a convolutional neural network (CNN) which is widely used in deep learning for IED detection (Lourenço et al., 2021; Tjepkema-Cloostermans et al., 2018). Its primary component are so-called convolutional layers which "extract information using filters that are iteratively convolved with the input." (Lourenço et al., 2021, p. 1439). The model has already shown to correctly identify IED shapes and to successfully discriminate between IEDs and other abnormalities (Lourenço et al., 2020).

Furthermore, the CNN model, more precisely the VGG model which is a subtype of CNN architecture (Goswami, 2020), has been adapted for the detection of IEDs since it was initially developed for the purpose of image analysis (Lourenço et al., 2021; Lourenço et al., 2020). Figure 11 shows the neural network's architecture in form of its building blocks. Put into simplistic terms, convolution refers to applying certain filters to extract only relevant information from an image, whereas pooling means to reduce the information in an image while at the same time intensifying the convolved features (Zafra, 2020). Therefore, a CNN mainly consists of sequential convolution and pooling layers (Zafra, 2020).

Since the AI-driven model is used to aid diagnostic decision-making, it can be classified as an intelligent clinical decision support system, as described in chapter 2.2.

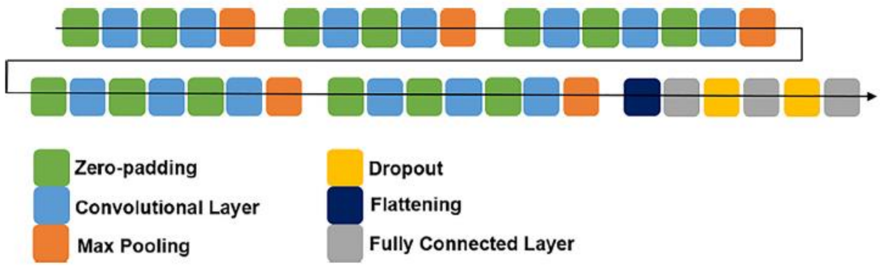

Figure 11: Depiction of the CNN architecture of the AI model for IED detection, as adopted from Lourenço et al. (2021) based on Lourenço et al. (2020).

4.4.4 Functionality and output of the AI system

To assist in the diagnosis of epilepsy, the AI system's analysis results need to be made accessible to the user. The AI model for detecting IEDs is integrated with other AI algorithms based on machine learning to arrive at a set of outputs that support the visual EEG review. Specifically, the system starts with some quantifications of generic EEG features in the EEG background pattern by using feature extraction based on machine learning. As mentioned by the developers in the team, feature extraction is not a newly developed AI method and the primary focus in this study lies on their novel AI model developed to detect epileptic discharges. In this latter AI model, according to the developers the EEG is first automatically divided into two second epochs, thus short EEG segments, which go into the deep learning model that detects IEDs, as further described in chapter 4.4.3, meaning that the model inspects the EEG data every two seconds for interictal epileptic discharges.

To get the AI system started, the user sits in front of a computer and first choses the particular EEG that is supposed to be analysed from the EEG database and converts it into an EDF file format. The file is then saved in another directory the AI system can access and right after the user starts the system for analysis. For a routine EEG, the system usually takes one to two minutes to run the analysis during which the user waits for the results to arrive, but for an ambulatory EEG it takes around 10 minutes to receive the results as the EEG recording is much longer. The results are automatically generated in a PDF file which contains the following outputs:

In the first part of the report, maps with general EEG properties are displayed which quantify the EEG background pattern. These maps give the user an overview and help in overall EEG interpretation and the diagnosis of an epilepsy syndrome. They for example allow to see whether the alpha rhythm is normal, the differentiation between the front and back of the brain is good or whether the overall frequency in the brain regions is abnormal such as too slow, fast or asymmetrical between the two hemispheres (Wang & Yan, 2021).

Below this part, a short interpretation of the maps is shown which is automatically text generated. For instance, the text includes a description of the alpha rhythm's frequency and symmetry, of the quality of differentiation between brain regions such as the left and right side as well as whether the brain is reactive to the patient's eye opening and closing.

This is followed in the report by the actual AI results. Firstly, the user can see the number of detected epileptic discharges and at what specific point in time in the EEG recording they are assumed to occur, with the discharges being indicated as stripes in a grey bar which represents the EEG. Additionally, the probability of each detection in an epoch actually being an interictal epileptic discharge is given with a score between 0 and 1. The probability threshold causes that all IEDs with a probability lower than the set threshold, for example 0.80, will not be flagged by the AI system. This threshold cannot be adjusted by the users as of now since this functionality has not been developed yet. Scrolling down in the AI report, each individual IED as found in the EEG is visually presented together with its probability and time of occurrence. The IED snapshots allow the user to see the shape of each suspected IED as well as its immediate surroundings in the EEG recording. To have a look at the AI detected IEDs in the EEG itself, the user has to navigate in the EEG viewer to the indicated time points.

To facilitate the review procedure of the AI detected IEDs, another option to view the results was recently introduced. The AI model for IED detection is now also integrated into the EEG viewer of the clinical EEG software the team uses. Specifically, by clicking on a button to start running the AI system, the assumed epileptic discharges are marked directly in the viewer where they occur and the probability of that detection being an epileptic discharge is indicated. Ultimately, the professionals can choose between the two options on how to view the AI detected IEDs.

4.5 The AI-supported epilepsy diagnosis pathway

In chapter 4.3.3, the work practices associated with reviewing EEGs at the neurology department without the help of the AI-driven decision support system were portrayed. Now, to understand how the use of this system impacts individual and collaborative work practices of the healthcare professionals, in the following it is firstly described in what ways they utilise and integrate the system into their work. Secondly, as laid out in the theoretical framework of this study, the perceived AI affordances and AI constraints giving rise to these usage practices are outlined. Additionally, the affordances are characterised as shared, collective or individualized. Thirdly, the present and future impacts on and changes in the professionals' work as reflected in the work characteristics *job autonomy and control*, *job feedback*, *skill variety and use*, *social and relational elements* as well as *job demands* will be elaborated on.

4.5.1 AI usage practices

In regards to the use of the AI system, no protocols, or user manuals exist for how to use and integrate the AI system into the professionals' work practices. Therefore, as shown hereafter, the AI usage differs not only between types of professionals but also between individual professionals of the same profession. Lastly, the terms 'AI result(s)' and 'AI finding(s)' in the following subchapters refer to the IED detections made by the AI system.

4.5.1.1 AI usage during a routine EEG review

When it comes to the use of the AI system during a typical routine EEG review, different usage practices were observed among the professionals. Among the residents, one of them described to either use it during the analysis when they are unsure about their observation and how to interpret it or when they are done with their analysis and want to compare their results with the AI system findings. If the first scenario is the case, the resident lets the system run for a few minutes in the background until the results are in. During the waiting time, the own analysis is continued or a short break is held. The following excerpt gives an impression of one of these usage scenarios:

> *"So this is […] on the left side on the back of the brain and […] two is on the right side and you want them to be quite similar […], they are not similar. That means that maybe something is going on. […] Um, you can see like this nice peak standing out of the rest. That's what we want to see. But mostly when I choose another part, it's not that obvious. And there's also like, this is a lot slower. Two hertz or three? Four. Um, so in this case, I would […] ask the AI to look at it as well because I'm like not sure if it's what I would, um, write down. So now I will export it to […] another file. So I'm converting it to another file and then I will open the, um, the program. Just check that it's in here. Yep, it is. So open the program and it will just run the analysis and it takes a while. So while it is running, I'll just continue with my own report and my own interpretation of it."* (R1)

Generally, when results in form of the AI PDF report are in, the resident checks the PDF from top to bottom, starting with the visualised EEG background features and going down to the AI detected discharges. If an AI finding that the resident hasn't found is deemed sensible or if an AI result deviates from the own interpretation and there's uncertainty about what is correct, the resident might put it into their report. Otherwise, the AI findings are not reported as no obligation exists to do so. After comparing the AI findings with one's own results, the resident writes the conclusion in their report.

On the contrary, the other resident reported to only make use of the first part in the AI PDF report which quantifies the EEG background and that they disregard the second part which shows the detected epileptic discharges. The reasons for this are examined in chapter 4.5.3 about the perceived constraints of the AI system.

Further, looking at the neurophysiologist involved in the routine EEG review as a supervisor, they reported to always run the AI system in the EEG viewer to skip through the detected IEDs in the EEG. Also, if a resident didn't use the system during their preliminary EEG review, the neurophysiologist makes sure to run the system during the discussion of the resident's findings out of personal interests related to the system's performance and potential future improvements:

> *[…] so I try to use it basically in almost all EEGs. Also to get a feel for it and, and get new ideas […]."* (N)

In other cases when the neurophysiologist reviews an EEG without the residents' groundwork, the AI is used by running analysis and subsequently going over its results to see whether they are in agreement with the system abouts its IED detections. Using the AI in this way is ascribed to an AI affordance which is elaborated on in chapter 4.5.2.3.

4.5.1.2 AI usage during an ambulatory EEG review

In terms of the AI system use during aEEG reviews, it was noted that the system is not used during the EEG analysis and report writing but rather after the technicians have fully completed their diagnostic report. While waiting for the AI results to come in, they usually tend to another task in the meantime as it takes a few minutes to receive them. After checking the AI results, they fill out an Excel list in which they note the EEG number, its reviewer, the patient as well as information about the AI system findings, such as the amount of IEDs found and their time of occurrence, and mention whether they deem them as correctly identified based on their own interpretation. Filling out this Excel file is the technicians' only purpose for using the AI system, they do not take its findings into consideration for their own analysis and therefore do not integrate its findings into their diagnostic report, as voiced by one of the technicians:

> *"[…] at this stage I'm only using it, uh, like in a scientific way. I do my job and afterwards I use the AI system to see if it's, um, compatible with my opinion on the results. […] so I see it doesn't affect my opinion because I already made my opinion on the, on the results."* (LT1)

The reasons for this are outlined in chapter 4.5.3, where the researcher dives into the constraints that the technicians see in the AI technology.

Furthermore, the function to view the AI detected IEDs in the EEG viewer instead of in the AI PDF report is used in an individual way by different technicians. One technician voiced that they mostly use this function with EEGs for which the AI detected many IEDs, as shown in the AI PDF report, because looking into the viewer gives a better overview and impression of the problem scope. Another technician expressed to always prefer looking at the marked IEDs in the viewer compared to the PDF report, as it facilitates comparison with the own analysis results, since they recognise the discharges from previously analysing the EEG.

Moreover, the results in the first part of the AI PDF report concerning the EEG background features are not used by one technician, which traces back to a perceived constraint as explained in chapter 4.5.3.

Looking at how the neurophysiologist involved in the system's development uses the AI system when checking the technician's work, the professional reported to still run the AI themselves to view the AI detected events next to the events marked by the lab technicians. The AI is run in the EEG viewer to skip through the AI IED detections. This is attributed to the same reasons mentioned in chapter 4.5.1.1.

4.5.2 AI system affordances

The above-described AI usage practices involve the actions and activities afforded by the AI technology. These usage practices give some first indications of underlying AI affordances. For example, the different usage practices between different types of professionals already indicate that collective affordances are present. Furthermore, it was found that some shared affordances were known by the team members to arise in the future when the AI system, particularly the IED detection, is further tested and developed. In addition, some AI affordances were desired as the system was perceived to lack certain useful functions. In the following, all identified affordances are described based on the data structure presented in Figure 5.

4.5.2.1 Shared & shared predictable AI affordances

Looking at the whole team of healthcare professionals, it was found that a number of affordances were shared by all observed and interviewed team members that either exist in the present or are predicted for the future. The latter, termed predictable affordances, are one of the main findings of this study and constitute an unexpected additional type of affordance.

Shared AI affordances

Sparse false negative IED detections

Among all team members, the AI system is deemed valuable to confirm EEG abnormalities in the form of interictal epileptic discharges as it usually detects all of them that occur in the EEG. Thus it was described that the amount of false negative detections by the AI system is low. In fact, all users expressed that they think the system is already good at doing so this early in its testing and development stage. Three professionals expressed this as follows:

> *"I think it doesn't miss the epileptic discharges, so that can be trusted."* (R1)
>
> *"[…] she is really, uh she really sees the […] epileptic discharges."* (LT1)
>
> *"When it does not [detect interictal discharges], there could be a limited sensitivity so it could miss a few. The likelihood is not very large."* (N)

Easy usage

Another point that was addressed refers to the AI system's user friendliness. Overall, the system was unanimously described as easy to use. The residents explained that once the action steps to take and buttons to click are learned, it would not be difficult and straightforward to make use of during their work. They expressed to be content with the fact that only a few steps are needed to get the AI system running its analyses. Similarly, the technicians acknowledged that it would be easy to use the system once they were familiar with the procedure of starting the AI analysis correctly. They also emphasized that learning which steps to take and how to interpret its output in the PDF file would be the only skills needed to be able to use it and once this is clear, its usage wouldn't be difficult. Further, the neurophysiologist involved in the development of the system emphasized how simple checking the AI detected IEDs in the EEG viewer is :

> *"So these are all the detected events. So you just click, click and then I say no, yes, no, I don't know, but I've seen a few already. So then I'm done."* (N)

Shared predictable AI affordances

AI-driven IED preselection

Considering expected future affordances, all team members included in the study predicted the AI to in the future allow them to check the AI detected IEDs instead of doing the visual analysis for IEDs throughout the whole EEG themselves. This was explained to be especially relevant for the technicians as they work with the hours-long ambulatory EEGs. One technician estimated that the AI system will reduce their EEG review time from now three to four hours to half an hour. According to the developers, the whole review might even be reduced to a few minutes, one of them giving the example of ten minutes. The technicians are convinced that the time they will win could be used on other tasks, as elaborated on in chapter 4.5.4.5, and the residents speculated about substantial time savings as well:

> *"[…] for shorter EEGs that are like 20 to 30 minutes and you can look at it for I think in five minutes you can have seen the whole EEG, maybe five, […] it's an estimation […]."* (R2)

Since the professionals predict to be able to only check AI detected IEDs in the future, they expect that this will reduce the number of pages and abnormalities they have to review for EEGs. The standard nowadays is that they look at each page of the EEG to detect abnormalities such as IEDs and since only a few seconds of the whole recording are displayed on each, the review necessitates rigorous work, particularly for the long aEEGs.

Improving IED detection

Across professions in the team, the AI system is expected to be contributing to an increase in the quality of patient care by improving IED detection which is nowadays subject to human error by reducing the number of incorrectly identified or missed discharges:

> *"I think you could miss less epileptic discharges […]."* (R2)

Generally it was described that this improvement has not taken place yet because the AI system is still in development and is now for the first time tested in practice since its recent implementation in the department. However, a resident argued that patient care is to some extent already positively affected, saying they think it happened a few times that the AI system detected epileptic discharges that the professionals themselves didn't find:

> *"[…] I think it happened a few times. And I think in that case that makes a difference […] for the better for the patients."* (R1)

Faster diagnosis

An important action that the technicians predict to be afforded in the future by use of the AI system is that they will deliver their EEG review results faster to the neurophysiologist in charge which means that a diagnosis can be made faster:

> *"[I think you could] get to a diagnosis sooner." (R2)*

This has important implications for work, as elaborated on in chapter 4.5.4.5.

Looking at the shared affordances that will be offered in the future, it is clear that all interviewed team members were knowledgeable about the overall purpose of the AI system and its future functionality and based on this indicated what they know the AI will afford in the future.

4.5.2.2 Collective AI affordances

Next to the shared affordances, collective affordances have been identified among different subgroups in the team, referring to the technicians, residents, the neurophysiologist and technical physician.

Checking EEG background properties

One collective affordance reported by several professionals concern the first part in the AI PDF report. The residents explained that it facilitates their EEG analysis as it enables them to see the EEG background in a visually compact manner, allowing them to grasp its properties at one look. They expressed this to be much easier than having to look page by page in an EEG to make sense of its background pattern. One resident emphasized that it is especially useful when two EEGs have to be compared, as they can compare the AI outputs for both side by side, using the AI as a back-up system to their visual analysis.

Looking at the technicians, one of them expressed that they like to use the first part of the AI PDF report to check whether the AI system came to the same conclusions in terms of the EEG background, such as the posterior-anterior differentiation and symmetry in the brain regions.

Moreover, the neurophysiologist also expressed to make use of this functionality as it allows to work more efficiently:

> *"And the background pattern part is integrated now with the AI system is also very convenient because it calculates a few things already for me, like the dominant rhythm and reactivity [of the eyes]. So some generic features and it even generates text."* (N)

Reassuring own IED findings

Referring to the AI system's IED detection feature, the AI system offers reassurance of professionals' own findings by being able to compare the IEDs found with the system's detected IEDs. This was found to be relevant for the residents in the team as they are training how to review EEGs and can use the AI output to back up their results. This feature is therefore described as a confirmation tool by the residents for their own IED detections.

Checking assumed IEDs

During EEG analysis, the AI system enables residents to check their assumptions of which observations are IEDs. Thereby the system can help them to come to a decision when they are unsure about whether a finding indicates epileptiform activity or not.

Rethinking own IED findings

A step further compared to receiving reassurance by the AI system is that it also can initiate professionals to rethink own findings when it finds an epileptic discharge that the professional did not see which was reported to mainly concern the residents as they are not as experienced in reviewing EEGs compared to the lab technicians and experienced neurophysiologists. For example, a resident referred to the system as *"another pair of eyes"* (R1).

Detection of different & less common IED types

Among technicians, the AI system was assessed to be good already in detecting various interictal epileptic discharges in EEG recordings, for example by stating the following:

> *"[…] you have different kinds of epileptic discharges in shape and the system also sees the ones that are less common already."* (LT1)

Another technician was deeming these AI detections to be very trustworthy, estimating that about 80 % of its results would already be correct.

Driving AI system development

Another observed collective affordance among technicians and the developers in the team was that using the AI's features serves to develop the system further. In fact, this was mentioned as the main driving factor for the technicians to use the system at this point in time. One technician explained that they deliberately use the system as it helpful for the developers to see the technicians' notes in the Excel file in terms of how good of a job the AI did in detecting the epileptic discharges in an EEG. Moreover, the neurophysiologist involved in the AI system's development uses the AI on as many routine EEGs as possible to learn about its performance and how to improve it in the future, as indicated in chapter 4.5.1.1.

IED viewing function in EEG viewer
Another AI affordance acknowledged by technicians and developers in the team is the option to view the AI detected IEDs in the EEG viewer. This function was described to substantially facilitate the professionals' work as it is less cumbersome and time consuming to directly look into the viewer instead of switching between the PDF report and EEG viewer to separately look up each IED from the report in the viewer. Also, it allows to look at an IED directly in its surroundings and with different filter settings and montages, allowing for an easier interpretation of the findings. This function is not used in the same way by each technician, as described in chapter 4.5.1.2, but in essence they are trying to reach the same goal which is facilitating their work and only accomplish this in different ways.

Laying the foundation for other research
Talking to the technical physician and neurophysiologist in the team who are developing the AI system, it became clear that testing it in practice and thereafter improving its performance serves the bigger purpose of building the foundation for other research projects that aim at improving epilepsy care, even going beyond diagnostics. The neurophysiologist described that the system opens new research possibilities as it affords to reduce the time and work effort needed for EEG analysis:

> *"Yeah. Because otherwise we say, oh, five recordings. That's way too much, no the AI will detect the events. We have the events and then we will do another technique [for another research project]. But the AI will help. So in this way […] if this would work, it would be a great shift because then you do really something new and you go further than only the diagnostics and you have time to do that because it's a new possibility actually that would be difficult to realize if you would not have an AI system."* (N)

4.5.2.3 Individualized AI affordances

AI-driven IED preselection
As explained above, a future shared affordance will be that the AI system selects the epileptic discharges in the EEG and the technicians check them. For the neurophysiologist, however, this seems to already be the case tom some extent as the professional uses the AI to make the detections instead of doing a full visual analysis:

> *"Okay. So it is really fast. […] so I have more time for other things. I still need to check it. It's not 100% perfect. When it does detect interictal discharges, I'm done. When it does not, there could be a limited sensitivity so it could miss a few. The likelihood is not very large. So I still. I don't completely rely on it yet. That's a little bit too early. Okay. Um, but still, it saves time because if it does detect IEDs, then I will look at those few and if I agree, then I'm done. I don't have to search for them."* (N)

Even though the AI makes the detections, the professional looks at the AI detected discharges to verify that they were correctly identified by the system which underlines the visual analysis as the gold standard still at this point in time considering that the system is still in development and makes mistakes. Further, it became clear that the specialist only needs to see a few epileptic discharges to be able to arrive at the specific epilepsy diagnosis for a patient. Thus, even though the professional is still testing the system's performance to drive its development, the AI is already saving the specialist time due to the way it is applied.

4.5.2.4 Desirable AI affordances

The following category of affordances has been coined based on AI system functionalities that the professionals in the team mentioned as useful to have as they would improve the system's applicability in a way that is valuable to their work.

Seizure recognition & differentiation

Looking at the residents, they voiced that the AI is not able to detect epileptic seizures, thus consecutive epileptic discharges, as they present in a slow wave pattern which the system is not able to recognize as a seizure. Epileptic seizures are a pivotal indicator for epilepsy and it was for example mentioned by a resident that it would be helpful if the AI was able to do seizure classification as it is based on a number of rules that have to be taken into account:

> *"[…] sometimes they are so frequent epileptiform discharges that we call it, uh, an epileptic seizure. Yeah. And sometimes it's hard to say is this a seizure or not? And that would also be nice if the AI can make a decision about that because […] there are rules on that […] so that would be cool."* (R2)

Further, the lab technicians also remarked that the AI technology would not be useful to detect seizures and one technician additionally noted that it could not differentiate between epileptic seizures and psychogenic non-epileptic attacks, which were referred to as PNEA by a technician, which is an important distinction to make to arrive at the correct diagnosis as the latter are symptoms of certain psychological conditions rather than of epilepsy.

Use on babies' & children's EEGs

It was voiced by several professionals that the AI-driven IED detection cannot be used on EEGs from children or babies as it has not been trained with their EEG data, yet. Apart from the developers in the team, the residents and technicians that use the AI system were aware of this limitation in the AI's applicability and presently only use it to support the analysis of adults' EEG data. Some professionals considered it as useful if the AI system could be used on EEGs of these population groups as that would broaden its usefulness for their work.

4.5.3 AI constraints

No different than with the above-described AI affordances, the constraints that the healthcare professionals perceive the AI system to entail also differ among types of professionals and individuals in the team, as outlined hereafter.

Unsatisfactory functionalities

- *Too many false positive detections*

Consensus became obvious among the residents and technicians in thinking that the AI's artifact detection and rejection is not good enough yet, meaning that it does not perform well in recognizing artifacts for what they are and misjudging many events in the EEG as an IED, for example breathing or eye movement artifacts. The number of false positive detections is considered high, with a resident giving the example of 200 IEDs being detected when only five of these are actually correct, making it hard to work with. In fact, one resident describes this as the most common issue:

> *"I think something is normal and the AI system says it's not normal. That's I think most often what happens."* (R1)

In fact, this constraint is the main reason why one resident does not use the AI's IED detection function, emphasizing that this function would be really extra compared to the EEG background quantification. In addition, a technician asserted that whether it is useful to run the AI system on an EEG depends on the quality of the recorded EEG signal which is only good when a stable, strong electrode connection is transmitted to the EEG amplifier since a bad connection leads to many artifacts in the impacted EEG channel, or channels, which would lead the AI system to falsely detect numerous of the artifacts as IEDs.

Looking at the developers in the team, they acknowledged that the system makes mistakes such as false positive detections, however do not consider this as that big of a problem compared to their colleagues since these detections could be acknowledged but not further regarded, as for instance expressed by the technical physician:

> *"Well, the AI system definitely marks also some artifacts. I mean, most artifacts are ignored by it, but there are some false positive detections, which is fine because then you only look at it […]."* (TP)

- *Missing IEDs due to probability threshold*

Another constraint perceived among the residents is that some epileptic discharges might not be detected by the AI system due to the set probability threshold:

> *"[…] so if, if the AI system thinks, […] that a certain discharge is with a little, uh, probability epileptiform, then it doesn't show it, for example. And we could have*

another opinion about that. So that could also […] so yeah, we shouldn't rely on it too much. Of course it should still be an add on I think." (R2)

Thus, this was considered another factor for why the visual analysis is indispensable at this point in time.

- *Poor readability of EEG background quantification*

One of the technicians declared to not be satisfied with the way the aEEG background properties are reported by the AI due to unsatisfactory readability. The professional perceived the visuals as overly crowded, making it difficult to find the EEG snippets in which the alpha rhythm is seen, detaining them from using this AI system feature altogether. They explained this as follows:

> *"[…] in a 24 hour EEG, you really have to look where does the patient have its eyes closed? And it's just tiny little pieces. So we have the, the little, uh, color, uh, scheme, uh it's just blue. This is not really that nice to look at. Sometimes it does. But I I like the [discharges]*." (LT2)

> *"[…] for the 24 hours […] it's really hard to find a good background. So we have […] the figure is just one big mess because you have no alpha."* (LT2)

Workflow impediment

- *Increased dependency*

Considering how the residents and technicians feel constrained in their usual workflow, it was found that the AI system is a 'black box' to them. This means that they lack insight into how exactly the system arrives at its results and how to solve technical problems in case of malfunctions. It was also voiced that the system sometimes simply does not work the way it is intended to. In some situations, this can be attributed to Internet connectivity issues, however that is not always the cause. This can be annoying, as described by a resident, because it requires them to reach out for help, hampering their workflow. The users report that this makes them dependent on the neurophysiologist/clinical neurophysiologist and technical physician in their team who develop the AI system. Several team members reported to usually try and run the system a few times, but if that remains unsuccessful, they contact one of the said developers in the team. If they are not available, the AI analysis cannot be resumed and is only continued after the expert had the time to fix the problem which can be on the next day. In the following, some of the team members' statements regarding this constraint are shown:

> *"Well, I wouldn't know, actually. Yeah, I really wouldn't know. It's for me, I It's really a black box what happens yeah. [N] knows which which strings to pull, but I don't know. […] Yeah, that also makes it quite dependent on [N] alone. Yeah, because that person knows most about it."* (R2)

> *"[…] I think what changed in the sense is that when it's, it's not working, we have to ask [the technical physician] a little bit more often. Like it's not working, can you have a look at it?"* (R1)

In addition, some professionals reported to sometimes be a bit more dependent on their co-workers than usual in situations in which they do not remember a step for how to use the AI system and therefore in most cases quickly ask a coworking colleague. Since no written usage instructions exist, as explained in chapter 4.5.1, asking colleagues is the only available option.

- *Limited visibility of IED viewing*

Regarding the residents only, it was observed that even though the IED viewing function in the EEG viewer is available to them, the residents were unaware of being able to use it themselves. For example, one of the residents stated:

> *"I only can look at the, file the pdf file and see this like small parts of the EEG. But I cannot go back to the EEG and look that specific part up."* (R1)

The residents expressed the wish to be able to view IEDs in the viewer to facilitate their work which shows that they were somehow not in the loop about this option existing already.

- *Extra time & workload for AI usage*

Among the technicians, a further constraint was found to be that the use of the AI system during their workday requires extra time and adds to their workload instead of reducing it. This was reasoned with the fact that they use it to support its development by filling out the Excel file after they are done with their own work. the technicians reported to not always have the time to run the AI system directly after a finished EEG review and that they rather prioritize finishing their visual analysis and forwarding their results to a neurophysiologist as soon as possible. The technicians stressed that ensuring good patient care is their priority and that they view the AI usage as separate from their required care activities, describing it as an 'extra' or 'attachment' that is used only when they have spare time to do so.

- *Limited AI skill set*

The technicians that work with the ambulatory EEGs considered themselves smarter than the AI system still since their skills are more experienced and less limited by being able to take a broader view when analysing an EEG, allowing them to detect other indicators of epilepsy next to IEDs as well as of other conditions such as sleeping problems. They think that the AI system has a lot to learn to become better to actually be good enough to support their own work.

4.5.4 AI usage impacts on work characteristics

Next to the actions and activities that the AI system can and cannot be used for by the healthcare professionals at the neurology department, the collected data also revealed how the present as well as anticipated afforded AI usage affects and will affect the characteristics of their work. In the following, the identified impacts on the professionals' *job autonomy and control*, *job feedback*, *skill variety and use*, *social and relational elements of their work* as well as on their *job demands*, as portrayed in the data structure in Figure 5, are unrolled.

4.5.4.1 Job autonomy & control

Present impacts on job autonomy & control

High discretion for work outcomes

Considering the residents' autonomy and control in their work, they emphasized that the system is just helping them at this point in time and that their visual analysis is still very much necessary. Thereby, they argue that they have high discretion in deciding on their work outcomes. The residents described that they are fully in control on deciding what to put into their diagnostic report and that they feel in charge of their work, showing themselves appreciative of having extra help in form of the AI as a confirmation tool.

Taking a look at how the lab technicians perceived their control over work outcomes, they expressed to still feel the same sense of autonomy over their work as before the AI system's implementation and expressed a feeling of superiority over the system in terms of their capabilities. For example, one technician stated that:

> *"I'm not convinced yet that [the system] is as good as I am to be honest. […] I also think personally [it] still has to learn a lot. And when [it] has learned more and I'm more […] acquainted with [it] than perhaps at, in the future, uh, and I don't know if it's a near future or far way future, I, I certainly believe that [it] can reduce my workload, but for now it's not the case yet."* (LT1)

AI usage expectancy

A difference in AI usage expectancy between the two groups was noted. As mentioned by a resident, even if the AI system is not always deemed necessary for one's own interpretation, it is still used to fulfill an assumed expectation and avoid disappointing the supervisor. Thus, even though the AI usage isn't explicitly communicated as mandatory, it might still be perceived that way:

> *"Um, it just like what I, I this example that I gave, like, um, there's no clear, uh, rule that you have to use it all the time or not. So sometimes maybe your supervisor expects you to use the program, and I did not. That's a little bit vague."* (R1)

The statement portrays that the resident feels conflicted when there's a mismatch between their supervisor's expectation and their own judgement of whether they need to use the system. On the contrary, the technicians were given full decision-making power about whether and when to make use of the AI system. Hence, the decision is up to each individual professional. Their usage goal is to support the system's development and they were not expected to use it to inform their own work at this point in time since the system is newly implemented and still in its testing phase.

Future impacts on job autonomy & control

AI supervisor function

Further looking ahead, there was consensus among the team members that they will not be replaced by the AI system but rather work together in the future. Specifically, the residents were sure that they will not become redundant for the EEG review but rather be needed to supervise the AI and have the last say in terms of making decisions during the EEG analysis, as indicated in their answers:

> *"[…] I think it's hard to leave the human out of there, definitely. […] Because it's also trained on human input. Um. Yeah. I think you will always need both. They will always need a human being on the end who makes the decision based upon the AI system. Yeah."* (R1)

> *"[I think] that we will be, um, yeah the supervisors of the AI, I think. Yeah. So it will definitely change. Yeah."* (R2)

These statements show that the residents expect to be supervisors of the AI who are responsible for checking the system's output, which conveyes the feeling of control over the AI system as the human is the one to judge its results and make final diagnostic decisions.

Regarding the technicians, they also showed themselves convinced that neither their analytic tasks with EEGs will be completely automated nor that they will ever be completely replaced by the AI someday:

> *"The computer can't do everything. That's not possible."* (T3)

> *"I think I think it's getting better. I think. Yeah, but I, I don't think you can ever have such an AI system without us."* (T2)

> *"[…] I personally, I don't believe that even if [it's] really good at it, uh, [it] [it] still has the same, um, quality level as, as myself. […] When you're like a human and you have a lot of, um, experience then you also are skilled. Um, and I'm, I have 20 years of experience, so I believe for myself that I'm skilled."* (T1)

These statements demonstrate that the technicians are confident in their expertise and do not believe that the AI will be superior to them in the future in the sense that it could do the EEG reviews completely autonomously. They are sure that the AI will always have to be supervised by them as it can still make mistakes, for example referring to the artifact detection:

> *"I think you always have to check because an EEG is so different for everybody. Mhm. And you know, I think the difficulty for an EEG, especially when people go home with it and come back, people do, you don't know what they're doing. So you have lots of, uh, uh, uh artifact. Mhm. So yeah, I think you always have to check, but I think it's going to in the future, it's going to save us a lot of time […].".* (T2)

This assertion implies the assumption that it will be difficult for the AI system to recognize artifacts correctly not only at present but also in the future, requiring a professional to go over the AI's results. Additionaly, the technicians mentioned to have qualities that the system cannot develop which was supported by the developers in the team, such as conducting the medical tests with patients and making them feel comfortable.

Increased difficulty in decision-making
On the negative side in terms of future impacts, supervising the AI could constrain the professionals' autonomy as this function can increase the difficulty to make a decision when the AI and professional disagree, as acknowledged among the residents. This is because the professional has no insight into the process of how the AI came to its conclusion, making it difficult to rely on it as it is not possible to backtrace its reasoning. This is described as follows by one of the residents:

> *"[…] maybe what if the AI system says, well, this is an epileptiform discharge and you don't agree with it, for example. So that could make things more difficult because then you have to think, hmm, what do I base this on that it is an epileptiform discharge. Yeah. And yeah. And, and then the golden standard is your eye."* (R2)

4.5.4.2 Job feedback

Present impacts on job feedback

Role clarity
The residents and technicians reported to not have experienced any changes yet in terms of how well they understand their tasks and role in the team due to working with the AI system. They reported that the system is not integrated into their work deeply enough yet at this stage to have an impact on how they perceive their role in the team.

Confidence building
In relation to the AI system's function as a confirmation tool for the residents, it was positively noted that the AI system enhances the feedback they get in their work and can thereby already help them to build confidence in analysing EEGs. Before implementation of the system in the

department, this kind of job feedback could only be given by their colleagues such as fellow residents and their supervisor.

Future impacts on job feedback

Role clarity
Again in terms of role clarity, some professionals anticipated that their understanding of their role will probably change in the future as the system will be more developed and more deeply integrated into their workflow, requiring the professionals to take over a different role as supervisors, as elaborated on in the previous chapter.

Training with AI
It is expected by the developers and technicians that the AI functions as a kind of additional training source for the residents and other inexperienced trainees, allowing them to more independently work by learning from the AI system, thus being less reliant on help from others such as their supervisor:

> *"One technician for instance said that "perhaps in the long term she can support, uh, colleagues or residents, for example, who are less, uh, experienced in looking at long EEGs. Then she can also support them."* (LT1)
>
> *"[…] maybe then [in the future] it says oh instead of neurophysiologist 1 saying, oh you miss something. Now the system is saying you miss something."* (TP)

Blind trust in AI results
In the more distant future, the 'black box' problem regarding the AI system that was associated with increased difficulty in decision-making could also negatively impact the quality of the professionals' job feedback as they will not receive clear information from the system about the work outcomes and how they came about, requiring them to simply trust the system's abilities, as expressed as follows by a resident:

> *"You have to trust […] what is given to you. So that's. That's hard because you are the end person that is responsible in the end."* (R2)

The technical physician also acknowledged that it would naturally feel scarier to trust the system more than a person even if it evidentially makes less mistakes than humans in the future.

4.5.4.3 Skill variety and use

Present impacts on skill variety & use

Little new skills & knowledge needed
Taking a look at how the AI system use influences the professionals' skill variety and use, it was observed that the knowledge and skills they need in daily work have not changed much, yet. In fact, they would only have to learn a few steps on how to access and operate the system so that it runs the analysis as well as understand how to interpret the PDF report output, referring to looking at the EEG background as a whole and comprehending the outputs about the IEDs. One technician's following statement reflects the overall sentiment about learning this in the team:

> *"It's not really difficult. Somebody has to learn to teach you what the buttons you have to push [are]. But then it's not difficult."* (LT2)

Future impacts on skill variety & use

Deskilling as potential threat
A potential negative future impact was addressed by the professionals that is best described as *deskilling*. What this loss of skills would look like was described differently between residents and technicians as shown hereafter in the sub-sections for this topic, each indicated by a bullet point.

- *Training staff in EEG review*

  One resident argued that the professionals could become deskilled in the sense that the AI overtakes the bulk of the EEG analysis and hence a lack of training in visually analysing EEGs arises. It could happen that they depend too much on the AI and do not sufficiently learn to analyse and interpret EEGs anymore, consequently also not being able to judge the system well, as explained hereafter:

  > *"So I can I definitely can foresee problems in the future when […] we will rely on this more and more, […] we are an AI system ourselves as well we also have to make hours and to, to see yeah, to see if something is an artifact or an epileptiform discharges or not. So yeah, we also need the hours of training and I think that could be a problem if the AI takes that over. We don't have the same training and we cannot really, um, be as critical towards the AI as we were used to. I think that could be a problem."* […] *Um, and, well, yeah, you could be really dependent on the AI system, which could mean that […] you cannot do it by yourself anymore. Yeah and, and maybe, uh, yeah, don't see, appreciate the […] errors that it possibly makes because it can still make errors."* (R2)

To avoid this scenario, the resident further emphasized that the professionals should still be able to analyse EEGs themselves in the future which was supported by the technical physician who stated that the residents will always have to look at the whole EEG to learn the EEG review themselves.

- *Learn technical background knowledge*

For the professionals to be able to stay in the loop, a resident expressed that all supervisors should ideally have foundational background knowledge of the system and that it would also be worth it to teach that to the residents as they are working in the department for several months. Apparently, not all supervisors have this fundamental knowledge as the system is not that widely applied in the department yet. Related to this, another resident expressed that it would be helpful for them to be able to solve issues that do not require programming skills, as this would make them less dependent on help from the system developers in the team.

- *Developing critical thinking skills*

Next to practicing the EEG analysis to prevent deskilling, a resident argued that professionals should acquire the skill of thinking critically:

> *"[…] Uh, yeah. Critical thinking skills. Yeah. Um, so I think you should always be in touch with how it is trained if you want to use it […] in your daily practice, you should know how it is trained and what […] it does make its […] decision upon. So you should know something about all the complex. Like, know at least something about all the complex, um, decision making, the AI does and […] what its pitfalls are. So that's, that's a new skill."* (R2)

As the quote shows, the basis for being able to think critically about the AI results would be to gain an understanding of how the AI functions, arrives at its decisions and what its weaknesses are.

- *Gaining skills in other areas*

As a positive byproduct of potentially losing some skills needed for EEG reviews, one resident acknowledged that becoming less trained in one area would imply to become more trained in another area, thereby allowing for insights into previously untouched areas.

Maintaining work meaningfulness

Regarding the technicians and their opinions on potential deskilling in the future, they did not voice the above described concerns and rather mentioned a different consideration. Technicians said that due to possibly having more time to spend with patients, which they on the one hand like, they would not want to lose the analytic work with the EEGs as they enjoy doing it:

> *"[…] analyzing the EEG is fun for us so you don't, you don't want to lose that."* (LT3)

The following example was given as the worst case scenario:

> *"[We would] only [be] there to put the stickers on the head and then take it off and that's it."* (LT2)

Thus, two contradictory truths held by the technicians were observed, which is that they on one side look forward to the support and significant ease of workload that the AI system promises, but on the other side wouldn't want to completely give up the EEG analysis. However, since they are confident in their skills and anticipate to always be needed to check the AI's outcomes as the system's supervisors, hence still being involved in the review process as the final decision-makers, they do not consider being redundant a realistic future scenario.

4.5.4.4 Social & relational elements

Present impacts on social & relational elements

Helping out co-workers

Looking at changes in the relational component of work, the professionals reported that they do not feel like how they generally interact with co-workers has changed yet upon AI usage. However, several professionals reported that from time to time they have to help a colleague out with a patient case, the AI usage or when they are deployed to introduce colleagues who have just started their residency to the AI system by explaining and showing them its functionalities. For the technicians this concerns helping each other out from time to time with using the system and being shadowed by newcomers while using the AI during their work as they are the experienced users compared to them.

Increased contact between users & developers

- *Support with AI usage needed*

Another change in the relational realm of the team is an increased contact between the users and the technical physician and neurophysiologist in the team who are involved in the AI system's development. This is because these two professionals are the contact persons for their team members when they experience system malfunctions or request help with any other issue concerning the system's functioning.

Moreover, the neurophysiologist functions as a direct supervisor for the residents. The amount of help needed turned out to differ from individual to individual. For example, one resident expressed to not need more help to come to their conclusions than before, whereas on the contrary, another resident mentioned that:

> *"I think sometimes for the first part [in the PDF report], you do need more help because it's so hard to grasp picture sometimes. So yeah, then you talk about that."* (R2)

- *Giving feedback on AI performance*

Additonally, another reason why the technicians have increased contact with the two professionals involved in the system development is because they are actively supporting their endeavours by reporting about the AI system's performance in the Excel file and will continue to be an important source of feedback to in the near future improve the system, as they are involved in the system's development.

- *Communicating AI changes*

In general, the professionals described that learning about system changes mainly happens through learning-by-doing, meaning by noticing that something has changed when using the system, or when talking to colleagues. In fact, only major changes are communicated by the developers in meetings with the team members, as acknowledged by one of the developers:

> *"Yeah. And I think if we really do a big change, then we also sometimes we once, I think or even twice uh, yeah did a educational session during the lunch for example, and that would really be [for] a big change. Then we would do that again."* (TP)

Future impacts on social & relational elements

Increased patient contact

Looking into the future, it was positively anticipated by residents and technicians that they will have more time for activities that instead of computer work involve direct patient contact, which they value highly and look forward to do more of, as emphasized in the following statements:

> *"I think the ideal situation would be spending more time with patients. Yes, because I think now we're still like we are spending so much time behind our computers and with all the administrations […], so it would be super, super ideal if AI saves us that much time that we just could look at the patient again."* (R2)

> *"[…] usually you're alone just with the patients. Which I think I love."* (LT2)

Sooner result delivery to patients

The team predicts that patients will receive their aEEG results sooner as the technicians will be able to do the EEG review faster and can subsequently deliver the results sooner to the neurophysiologist in charge. In that context, one technician mentioned the following:

> *"Now we have, like, at least three weeks between […] the EEG and the results to […] get to the patient […] and then maybe it's going to be in a week."* (LT2)

Less time with supervisor

For the future, a more drastic change was speculated by a resident, saying that residents might spend less time with their supervisors, thus even saving time apart from during the EEG analysis, as the AI system will already show them the abnormalities in an EEG, thereby having to discuss less about the EEG with a supervisor.

4.5.4.5 Job demands

Present impacts on job demands

Added work challenges
Related to the dependency on team members due to the lack of written instructions and inability to solve system malfunctions it was found that the challenges professionals are faced with are somewhat increased which adds to their job demands. They have to keep themselves informed about how to use the system through learning-by-doing when a system change occured or when they do not remember which button to push.

Increased time & work demand for EEG review
As of now, the technicians' job was described to be more demanding than before implementation of the AI as its use and the reporting about its performance increases their overall workload for now:

> *"Um, so for now, you can say […] [it] doesn't help me to reduce my time I spend, but actually, [it] […] takes time at this stage because it's still […] kind of scientific, experimental part for the […] part that I'm using it for."* (LT1)

Future impacts on job demands

Decreased time & work demand for EEG review

- *Performing more medical tests & aEEGs*

As touched upon in the context of job autonomy and control already, the AI system promises to reduce the healthcare professionals' workload and to save time in the future. Particurlarly the technicians are expected to benefit from this as their EEG analyses take hours. The time won can be used for other tasks, such as performing medical tests with patients and setting up more ambulatory EEGs than nowadays, as preceding routine EEGs wouldn't always be necessary anymore due to the shortened review times for aEEGs. One technician speculated to potentially be doing 80 % aEEGs and 20 % routine EEGs in the distant future. The technician also mentioned to not anticipate total replacement of routine EEGs, as the path from performing the EEG to providing the attending physician with the results can, if urgently needed, take about an hour with this kind of EEG since an experienced technician is able to simultaneously conduct and analyse the EEG.

- *Easing mental strain*

Additionally, the time won by automating the bulk of the EEG analysis in the future is expected to ease the mental strain weighing on the professionals, especially for the lab technicians as they are *"loaded with work"* (R2) which is amplified due to the lack of colleagues within their profession caused by a shortage of lab technicians in the Netherlands.

Increased responsibility for work outcomes
Taking a look at the professionals' anticipated future supervisor role from another perspective, professionals recognized that it comes with additional responsibility as they will be required to make sense of the AI system's output. A resident stated the situation as follows:

> *"Well yeah. Yeah. It comes with the responsibility of still understanding […] the program. Still understanding, uh, the, the bites that were given to you. So […] yeah, that I think it comes with a bigger responsibility."* (R2)

Overall, it was recognized that since the AI system is still in development, the demands in the professionals' job will change several times and will probably be different to some extent in a few months, most certainly in a few years time.

5. Discussion & Conclusion

In this chapter, firstly the most important findings of this study are discussed through the lens of literature whereby the research question is answered. To do so, the research question is divided into two parts, separately focusing on findings referring to how the work practices of the healthcare professionals in this case study are affected by their AI usage and secondly on results answering how their collaborative work has been impacted by it. In a following section, the overall impact of the AI use on the professionals' work is considered. Subsequently, the theoretical and practical implications, recommendations for clinical practice, limitations of this research as well as directions and opportunities for future research are presented.

5.1 Learnings from AI affordances, AI constraints and AI usage impacts on work

5.1.1 Work practices: Why the future affects the present and how the present is shaped

Looking at work practices first, one main finding refers to predictable affordances. Specifically, the results indicate that some shared affordances and associated changes in work were predicted for the future when the AI system is further developed and integrated into the team members' workflows, however, these predictable affordances seem to affect the professionals' work already as they influence their perceptions and usage of the AI system in the present. How the AI is and will be used in turn impacts the professionals' present work, as illustrated in the adapted research model in Figure 12. Looking at literature, it is argued that predictable affordances can be considered a new addition to the theory of affordances as it has not received any scholarly attention yet (Leonardi, 2011; Kaur et al., 2018; Kaur et al., 2020; Johannessen, 2023; Nagy & Neff, 2015). Instead, for example Nagy and Neff (2015) conceptualized a new type of affordance termed imagined affordances which refer to expectations for a technology as imagined by its users. Moreover, several studies have investigated the concept of anticipated affordances which are defined differently by different scholars (Kaur et al., 2018; Kaur et al., 2020; Johannessen, 2023). For instance, in the context of social media posting decisions and behaviours, anticipated affordances were conceptualized as affordances that people perceive in the social networking sites they use

(Kaur et al., 2018; Kaur et al., 2020). In a different way, Johannessen (2023) defined anticipated affordances as those actions that people expect an AI technology to allow them to do without having any prior usage experience with it. In that study early reactions to a telepresence robot were investigated, arguing that anticipated affordances build the foundation for people's reactions to a technology once its implemented as well as for whether and how they perceive its so-called actual affordances once they come in touch with it (Johannessen, 2023). Even though the aspect of evaluating an AI technology for its future use overlaps with the notion of looking into the future in this study, the striking difference is that the professionals in this case study already have had usage experience with the system as it has already been implemented. Thus, the findings further suggest that predictable affordances are applicable to AI that is already in use but still in development, for example when it is used in a (clinical) validation phase.

According to literature, the perception of predictable affordances might depend on knowledge about the AI and its purpose. This makes sense, firstly considering that understanding the AI's purpose is an essential component of comprehending the technology (Makarius et al., 2020) and secondly because prior research has shown that perceptions of AI technologies are based on what people know about and expect from them (Makarius et al., 2020; Klein & Heuser, 2008). Consequently, the extent to which a professional is knowledgeable about the AI and its present and future functionalities could influence which predictable affordances are perceived besides whether these are perceived at all. In addition, this theorized relation between knowledge about the technology and perceived affordances is somewhat supported by Zawacki-Richter et al. (2009) who studied mobile learning and its potential as a new learning method for distance education, amongst other things looking at affordances that distance educators expected mobile learning to offer. They found that the perceived affordances were dependent on having knowledge about and experience in mobile learning, showing that most people who were personally involved in this teaching method positioned themselves positively by affirming that it can create new possibilities for learning and teaching.

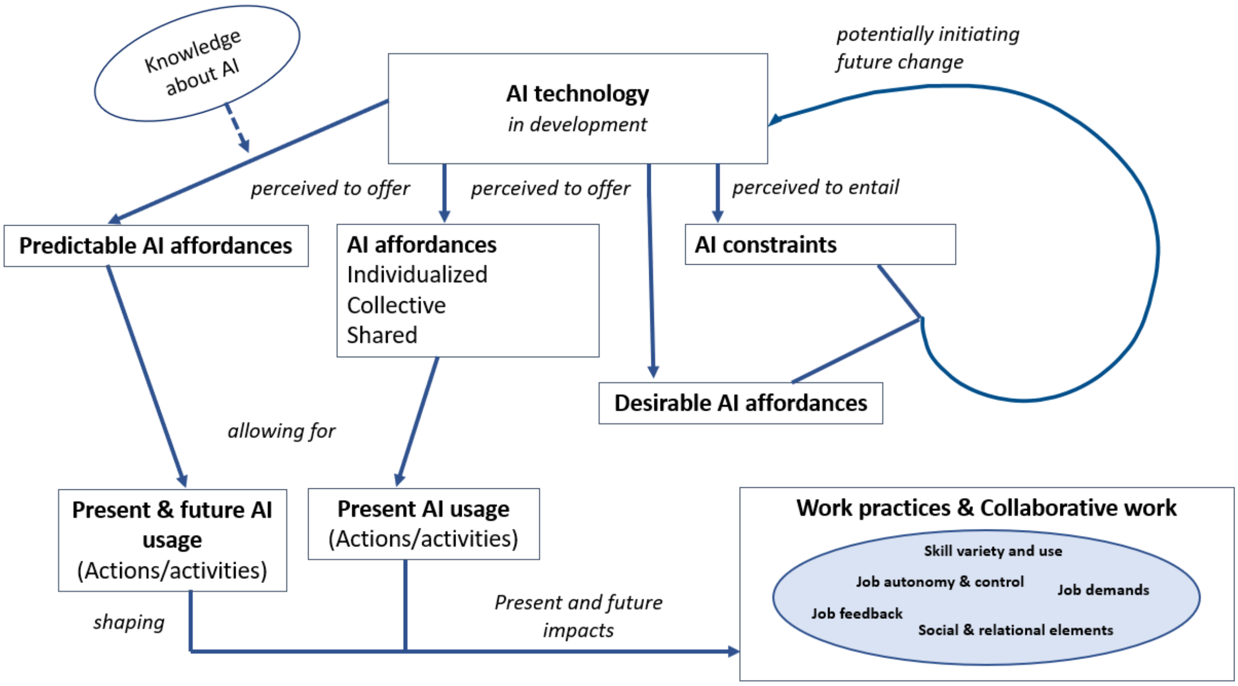

Figure 12: Adapted research model based on study findings. The perception of predictable affordances is suggested to depend on 'Knowledge about AI'.

Further considering the role of knowledge in this study, it was found that the neurophysiologist in the team involved in the development of the AI used the system in an advanced manner compared to the other team members. This could be attributable to the fact that the professional has in-depth insights into the system's functioning as they were involved in its development from the start up to its current version, making it easier to trust the system as it doesn't appear as a black box (Parker & Grote, 2020), which contrasts the experiences of other team members. Thus, it is argued that the level of knowledge about the AI influences the trust put into it (Parker & Grote, 2020), affecting what AI affordances are perceived.

The last consideration to be made about affordances is the additional category of *desirable affordances*. Other studies have already looked at affordances that people desire in a technology, for example as input for building prediction models for social media posting behaviour (Kaur et al., 2018; Kaur et al., 2020). Since desirable affordances imply a current lack of functions, it can be asserted that they implicitly indicate desired changes in the AI technology, as illustrated in the adapted research model in Figure 12.

Furthermore, study findings show that an individuals' AI use depends on how they perceive the technology and its features. Technology perceptions have already been widely established as precursors for technology adoption and use in a healthcare setting (Lu et al., 2005; Morilla et al., 2017; Gagnon et al., 2015; Lin et al., 2011). For instance, the Technology Acceptance Model (TAM) which asserts perceived usefulness and perceived ease of use as determinants of technology acceptance, as well as perceived barriers to technology adoption have been extensively studied (Lin et al., 2011; Davis et al., 1989; Ma & Liu, 2004). Considering that all professionals in this study reported to experience restrictions in work that come with the AI usage, referring to the identified AI constraints, their AI perceptions were not only positive but also negative. For some professionals, certain perceived constraints even prompted them to not make use of the respective AI features in their work as they seemed to hamper them too much in their work. This supports the finding in literature that *how well* professionals adopt AI-systems largely depends on the way they are integrated into their workflows and processes (Petitgand et al., 2020). Even a step further, the study showed that if the AI system is overall considered not good enough in terms of functionality by certain healthcare professionals, they abstained from using it to inform their own work altogether. This can be related to studies in the field of healthcare information technology that have discovered healthcare professionals such as physicians evaluate a system primarily based on its utility and functionality instead of other aspects such as ease of use (Chismar & Wiley-Patton, 2003; Keil et al., 1995; Chau & Hu, 2002; Lin et al., 2011), implying a direct link between whether a system is perceived sufficiently useful for completing their daily work tasks and their technology acceptance (Lin et al., 2011). As with the desirable affordances, perceived AI constraints communicate favourable changes to be made in the AI technology.

Another notable finding is that even though a number of affordances were recognized among all professionals, a number of different affordances were perceived by different groups of professionals, referring to the collective affordances, implying different AI usage practices. Thus, the type of profession a user had influenced the ways the AI system was used. In other cases, collective affordances referred to several professionals from different groups, such as the affordance of being able to conveniently check the background properties of EEGs by using the AI system. These findings relate to results of previous studies, as accounted for in the theoretical framework, which found that different actors can perceive different affordances in the same technology (Islind et al., 2019; Leonardi, 2013). This is because the affordances a technology offers depend on each user's perceptions of its material properties (Leonardi, 2011). Additionally, seeing how differently the AI system was used supports literature which theorizes that effects of the AI-technology are not fixed and rather determined by the way it is developed and deployed, meaning that the technology's impact on work can be actively influenced (Parker & Grote, 2020; Leonardi, 2012). This also implies that perceived AI affordances are subject to change in the future when the team members are faced with new system features.

Another major study result refers to the team members' expectation to take over a supervisor role for the AI system in the future. This is a commonly described future scenario in scientific literature that deals with the future of AI in work (Parker & Grote, 2020; Sheridan, 1978). The professionals expect to remain the final decision-maker over diagnostic decisions made in the context of EEG reviews, thus taking the stance that the AI will support them. However, decision-making and intervening in case of malfunctions could become more difficult due to a lack of insight into how the system arrives at its results, which is a common problem associated with AI usage as described in literature (Parker & Grote, 2020).

Moreover, related to the professionals' skill variety and use, the potential threat of deskilling was thematized. A popular scientific perspective on this phenomenon is that workers will lose skills for tasks they are not required to do anymore since these will have become automated, leading to the deskilling of workers and blurring the lines for their responsibilities in the workplace (Parasuraman & Manzey, 2010; Skitka et al., 2000). If for example work is deskilled by a technology, most likely learning- and motivation-related outcomes among employees are reduced (Parker & Grote, 2020). The results of this study confirm such concerns as they were voiced among residents. In contrast, the technicians were rather concerned with maintaining the EEG analysis as an integral part of their job which is an unexpected finding, since many studies emphasize that AI-based technologies can allow healthcare professionals to focus on the more difficult and meaningful tasks by executing simpler routine jobs (Parker & Grote, 2020; Beam & Kohane, 2016), thereby creating a favourable change in work for professionals. Thus, based on literature it is argued that if the task is integral to one's work, thereby making work meaningful (Hackman & Oldham, 1980; Parker & Grote, 2020), more resistance is shown towards the AI system usage. Moreover, the technicians were observed to take pride in their skills and capabilities, arguing that the AI will not replace them due to the diversity of their tasks and the system's proneness to mistakes that require supervision. This is in line with Aleksander (2017) who asserts that training skills related to judging AI outcomes could help to diminish fears surrounding an AI system. Further, the findings are supported by scholars who predict that more likely only some tasks will be replaced instead of whole jobs (Parker & Grote, 2020; Shneiderman, 2020) as the work of professionals is deemed too complex and multifaceted for machines to simply replace them (Davenport & Kalakota, 2019).

5.1.2 Collaborative work: More we, less me and human-AI collaboration

Considering how the healthcare professionals' collaborative work has been impacted by the AI usage, several present and anticipated changes in the dynamics and relationships between professionals in the team and with patients have been identified. Particularly notable is the increased dependency of the technicians and residents on the developers in the team, as they reported to usually not be able to resolve system malfunctions themselves and have to ask for their help to resume their work with the AI. It can be argued that the lack of usage rules and written instructions amplifies this dependency. The amount of help needed was found to differ from person to person, depending on their experience with and knowledge of how to work with the AI. Being dependent on the developers influences the professionals' autonomy as this reduces their decision-making power over their own work (Parker & Grote, 2020). However, in fact, a mutual dependency between these users and the developers can be inferred, as the developers in turn voiced to depend on their team members' feedback on the system's performance to further train and develop the system in the future. This constitutes a significant change in team relationship dynamics as these two types of professionals were not directly working together due to the nature of their daily tasks before introduction of the AI system. In general, asking for help with the system and communicating about it in the team was found to take place informally, for example when the professionals asked their co-workers in case they did not remember which step to take to run the AI analysis.

Moreover, the finding that residents could get feedback from the AI on their own work has changed dynamics in the team in the way that before implementation of the system this kind of job feedback could only be given by colleagues such as fellow residents and their supervisor. At some point in the future, the AI was expected to be used as a training tool for the residents, thus it is argued that the AI will surpass its support function since it will function more like a teammate that takes on an advanced role which was previously reserved to humans (Gladden et al., 2022). This consideration is strengthened by the potential future development that residents might spend less time with their supervisor as they can work more autonomously due to learning from the AI system. The AI taking the role of a co-worker could impact the professionals' well-being, motivation and performance in yet unknown ways (Ötting, 2020). Further, on the one hand this implies that more efficient work is possible (Parker & Grote, 2022), but on the other hand it would reduce human collaboration which comes with advantageous ways of communicating and relating that are unique to humans, such as intuitive decision-making and dealing with equivocal situations (Jarrahi, 2018).

Lastly, it is noteworthy that spending more time with patients and delivering their test results faster in the future through more efficient collaboration between professionals is likely to enhance the team members' task significance, as these changes in their work contribute to substantially improve the patient care process (Hackman & Oldham, 1980; Parker & Grote, 2020).

5.2 Overall AI use impact on work: The AI as an assistant

Based on the categorisations of overall AI use impacts on healthcare work described in the theoretical framework in chapter 2.4, as proposed by Pee et al. (2018), it is argued that the ICDSS the healthcare professionals in this case study use impacts work by offering *assistance*. Specifically, it can assist human work by reducing the cognitive workload needed to review EEGs. This implies sharing the cognitive load between humans and the AI, thereby constituting it as a collaborator that requires direct interaction with humans to help them in their work (Pee et al., 2018). However, as the system is in its first clinical validation phase and still being developed, it has not replaced visual analysis by the professionals, yet, thus the intended end use will occur in the future. Nevertheless, it is already actively supporting some of the team members in clinical practice. Going a step further than assistance, it is argued that the more complex the AI system becomes by being further developed and enhanced by new features, the more intertwined it could become with humans in a symbiotic relationship, which would imply an increasing dependency of humans on the AI system and an even more profound impact of the AI on work (Makarius et al. 2020).

5.3 Theoretical implications

This qualitative research on the real-life use of an intelligent decision support system in a healthcare setting contributes to scientific literature on AI use in healthcare teams in a number of ways. Even though AI systems and their usefulness for aiding clinical decision-making are often studied (Knapič et al., 2021; Gonzalez-Smith et al., 2022), this mostly happens on a theoretical level as studies on the use of AI technologies in work environments of healthcare professionals are lacking, implying that the actual effects of AI use on the characteristics and quality of work remain unknown. This case study adds to theory by exploring how the work practices and collaborative work of healthcare professionals is impacted by their AI usage through the lenses of affordance theory and work characteristics. Based on the findings, four important implications for theory are identified and discussed in the following.

First, affordance theory as conceptualized by some scholars (Leonardi, 2011; Leonardi, 2013; Gibson, 1986; Volkoff & Strong, 2013; Johannessen, 2023) is on the one hand supported and on the other hand proposed to be extended by a new contribution. In terms of support, Leonardi's (2013) conceptualization of shared, collective and individualized affordances was applicable to this research and has shown itself to be useful for revealing AI affordances in the team, uncovering that the AI is perceived and consequently used in certain similar ways but also differently on a group and individual level among team members. In addition, the theoretical notions that technology affordances depend on users' perceptions of its features (Leonardi, 2011) and that these affordances can be actualized differently by different users (Volkoff & Strong, 2013) are supported. The results further underpin the research by Parker and Grote (2020) about AI impacts on work characteristics which underscores that the effects of AI usage are not predetermined but rather dependent on a number of different factors related to the individuals and their relationships, the technology itself and the higher-level context such as organisational and occupational factors. Moreover, in line with Johannessen (2023) and others, this study acknowledged the importance of considering affordances expected for the future, however in a different way than those prior studies by arguing that predictable affordances will not only influence future work but also influence current work. The concept of predictable affordances is proposed as a new addition to the theory of affordances as it has not received any attention yet in literature. Future studies are needed to further investigate this concept for its potential validation in the same particular context of comparable AI technologies that are still in development.

Second, this research supports Makarius et al. (2020), Petitgand et al. (2020) and other scholars by firstly underlining that AI perceptions largely depend on what people know about and expect from an AI technology, reflected in the assumed connection between knowledge about the AI and the perception of affordances, as well as by showing that how well professionals adopt AI-systems largely depends on the way they are integrated into their workflows and processes (Petitgand et al., 2020; Makarius et al., 2020). Consequently, this study emphasizes that future studies should further address the role of AI perceptions, AI acceptance and usage when studying how work is impacted by implementation of an AI system such as an ICDSS.

Third, next to supportive findings, this study also resulted in an insight that contradicts other research, referring to the technicians that voiced reluctance towards potentially handing over the EEG analysis to the AI in the future as they enjoy it. This opposes other studies which emphasize that AI-based technologies can allow healthcare professionals to focus on the more difficult and meaningful tasks by taking over repetitive, time-consuming and routine work (Parker & Grote, 2020; Beam & Kohane, 2016; Pee et al., 2018), thereby creating a favourable change in work for professionals. Thus, this result suggests that it is not a given that professionals gladly hand over tasks to AI, even if objectively one would judge these to be unpleasant. This surprising result should be explored further in future studies as it promises to add relevant insights to literature on AI implementation, acceptance and usage.

Fourth, a study finding that extends existing theory, at least partially, is that of desirable affordances. Other studies have already looked at affordances that people desire in a technology, for example as input for building prediction models for social media posting behaviour (Kaur et al., 2018; Kaur et al., 2020). However, the relation between desirable affordances and their implicit indication of desired changes in an AI technology that is already in use, as postulated here, should receive scholarly attention as well as it could reveal how a technology should be improved to be more useful or user-friendly.

5.4 Practical implications

This case study's findings add value for clinical practice by making a number of contributions relevant for developers of intelligent decision support systems applied in clinical settings and even of other healthcare AI technology as well as for hospital (department) managers. Firstly considering developers, the usefulness of affordances for informing the development of an AI system is emphasized by this study. Specifically, learning about the actions and activities that the features of a system allow users to do informs those in charge of its development whether they have constructed it as intended. In addition, affordances can shine light on potential AI usage practices that were not accounted for, but are innovative ways the system can be used in. Moreover, AI constraints and desirable AI affordances inform about changes that should be made to the system to improve its usefulness and user-friendliness, or even allow its use in the first place depending on the perceived degree of restriction in work. Learning from affordances and changing the technology according to what bothers its users or based on which functionalities would upgrade its functionality aids in developing and adapting the technology to the users' needs, shifting the focus from the technology to human workers (Sujan et al., 2022). Ensuring a fit of the technology ensures that the AI actually unburdens healthcare professionals rather than overwhelm them (Kaasinen et al., 2022) and allows for its effective use (Parker & Grote, 2020). Moreover, developers can benefit from knowing about the investigated relationship between AI affordances and AI use impacts on work characteristics, as tracing back to these user perceptions helps understanding how observable effects on work came about.

Secondly, these case study findings are also of use to managers in hospitals who are responsible for introducing their employees to a new AI technology and for leading its implementation process. They should be aware that how they frame the AI, communicate and educate about it shapes their employees' expectations and preconceived ideas about the technology and in the subsequent implementation process, employees need to be given the necessary resources to integrate the AI effectively into their work, as supported by Makarius et al. (2020). As shown in this study, it is important to communicate the AI system's purpose, current and future development to all involved professionals as this influences how they perceive the AI in the present and what they expect from it in the future, both influencing how they use the AI in the present. Furthermore, this study suggests that AI usage rules and written usage instructions are helpful resources to offer to employees as the lack thereof can make AI use cumbersome or more difficult.

Overall, developers and managers alike should keep in mind that the initial use of an intelligent decision support system and its development already have tangible implications for the healthcare professionals' current individual and collaborative work characteristics, as the results in this research show.

5.5. Limitations

A universal truth in research is that every study has limitations, mainly based on its research approach and design. In the following, the limitations of this thesis are outlined. To begin with, two limitations refer to the data's trustworthiness in this study. Firstly, not all team members that have worked with the AI system before could be recruited for participation. Two other healthcare professionals with AI use experience in the team were unsuccessfully reached out to which led to a smaller number of study participants than anticipated which is significant considering that the healthcare team under study was small to begin with. Secondly, not all professionals that participated were willing to take part in an observation session as well as an interview and instead preferred to only take part in an interview. This limited insights into their work on learnings from the interview sessions.

Further, this research has been conducted as a single case study which does not allow for generalization of its findings to other research contexts, requiring the validation of results by future studies looking at healthcare teams in comparable hospital settings. Nevertheless, as the nature of the chosen research design implicates, the research purpose was to in an exploratory manner derive insights into the topic of interest as opposed to testing theory.

To mitigate the negative effects of these limitations, a few measures were taken when designing the study. Firstly, member-checking was applied to avoid misinterpretations of data by asking key stakeholders in the team, referring to the two professionals developing the AI system, for feedback on findings regarding the department, team, the epilepsy care process, associated work practices and descriptions of the AI system and its functionalities. Questions for clarification were asked, for example in terms of data anonymity, and feedback was received in form of written comments. Secondly, data triangulation was applied to improve the study's quality (Igira, 2012; Rogers et al., 2004) by making use of observation sessions while taking field notes, semi-structured interviews, meetings and a thorough analysis of scientific and non-scientific online sources and documents. Lastly, a code of conduct and confidentiality statement were signed before the start of data collection to ensure the researcher's professional behaviour and confidential data handling.

5.6 Recommendations for clinical practice

Based on the results of this study, a number of recommendations can be made for the two developers of the AI system, who at the same time are responsible for its implementation, in the team subject to this case study. Those are considered in the following.

Firstly, it is advisable to involve the team members in the development of the AI system by taking into account their perceptions and first usage experiences to ensure their adoption and use of the technology as end users. It is recommended to take note of the constraints they perceive the AI to entail and the functionalities they desire for further system improvements. This is especially relevant to in the future be able to convince the technicians of the system's capabilities. Further, written resources could be offered to the team such as a user manual for the AI system and a description of its functionalities which could not only help current team members but also newcomers such as trainees that have to work with the AI.

Another recommendation refers to keeping the team members in the loop about further system developments, as they have certain expectations concerning what the AI system will allow them to do in the future. Communicating planned changes as well as new future system developments that affect the end users is important so that they can form ideas about its impact on their work and meaning for their role.

Thirdly, it should be ensured that the professionals will be well-prepared for taking over the role of AI supervisors in the future. This function not only requires knowledge about the AI system and an understanding of its functioning, but also an experienced eye to be able to make qualified judgements about the AI's outcomes to inform epilepsy diagnostics. Therefore, it is recommended to educate all professionals that are using or will use the system about how the system is built and functions as well as to train them in judging its output. This is particularly recommendable for those that supervise residents and for the residents themselves. Fostering knowledge and use experience goes hand in hand with preventing deskilling.

5.7 Future research

Taking a step back to overarchingly look at the findings of this study, several possibilities and interesting directions for future research arise, as elaborated on in this chapter. One of the main future research interests should be the suggested predictable affordances, as further studies are needed to substantiate this newly postulated concept. In that context it would be relevant to investigate whether these types of affordances are found among other healthcare teams who use an ICDSS that is still in its development and testing phase. Additionally, the questions arise whether these affordances are applicable to other types of AI technology and if healthcare professionals also perceive them in AI that is mature, meaning in its definite end-stage or at least with no further development in sight. Further, referring to the theorized relation between predictable affordances and knowledge about the AI, it would also be important to conduct studies that build on this research to see whether this case-specific result can be validated or not under similar conditions.

Moreover, another recommendation for future research is to study how the perception of an AI system, such as the one subject to this study, and its features change when the technology has been adapted based on perceived AI constraints and desirable affordances communicated by healthcare professionals. How does this influence previously identified affordances and associated AI usage? It would be valuable to perform a study that follows a healthcare team over a longer period of time and examines how perceived affordances change over time with the development of a system and how the changes in AI and healthcare work continuously and alternately impact each other.

Another fruitful research avenue concerns collaborative work and the question of whether the observed increased dependency of team members on the developers would not exist or look differently in another similar setting in which more resources are available to the team such as background information on the AI's functionality and a user manual.

5.8 Concluding remarks

In conclusion, this exploratory research provides insights into the real-life clinical use of an intelligent decision support system in a healthcare team with the purpose of supporting EEG reviews for diagnosing epilepsy, thereby assisting human work. The main study findings offer a multidimensional answer to the research question. They show that (1) even though the AI system was not in its final state yet, its development and initial use already had tangible implications for the healthcare professionals' current work. Moreover, (2) the new concept of predictable AI affordances was suggested, referring to affordances that AI users predict the AI to offer in the future based on future system developments. Furthermore, (3) it was found that besides shared affordances, collective AI affordances were perceived by different groups of and across groups of professionals, meaning that the AI use differed among professionals. This study also revealed (4) that the individuals' AI use was dependent on how they perceived the technology and its features, highlighting that its effects were not predetermined, as AI constraints led to not making use of AI features or the whole system for their own work and therefore indicated changes to be made in the AI. Overall, the AI already took an assisting role in the work of some professionals and was expected to fully fulfill this role in the future.

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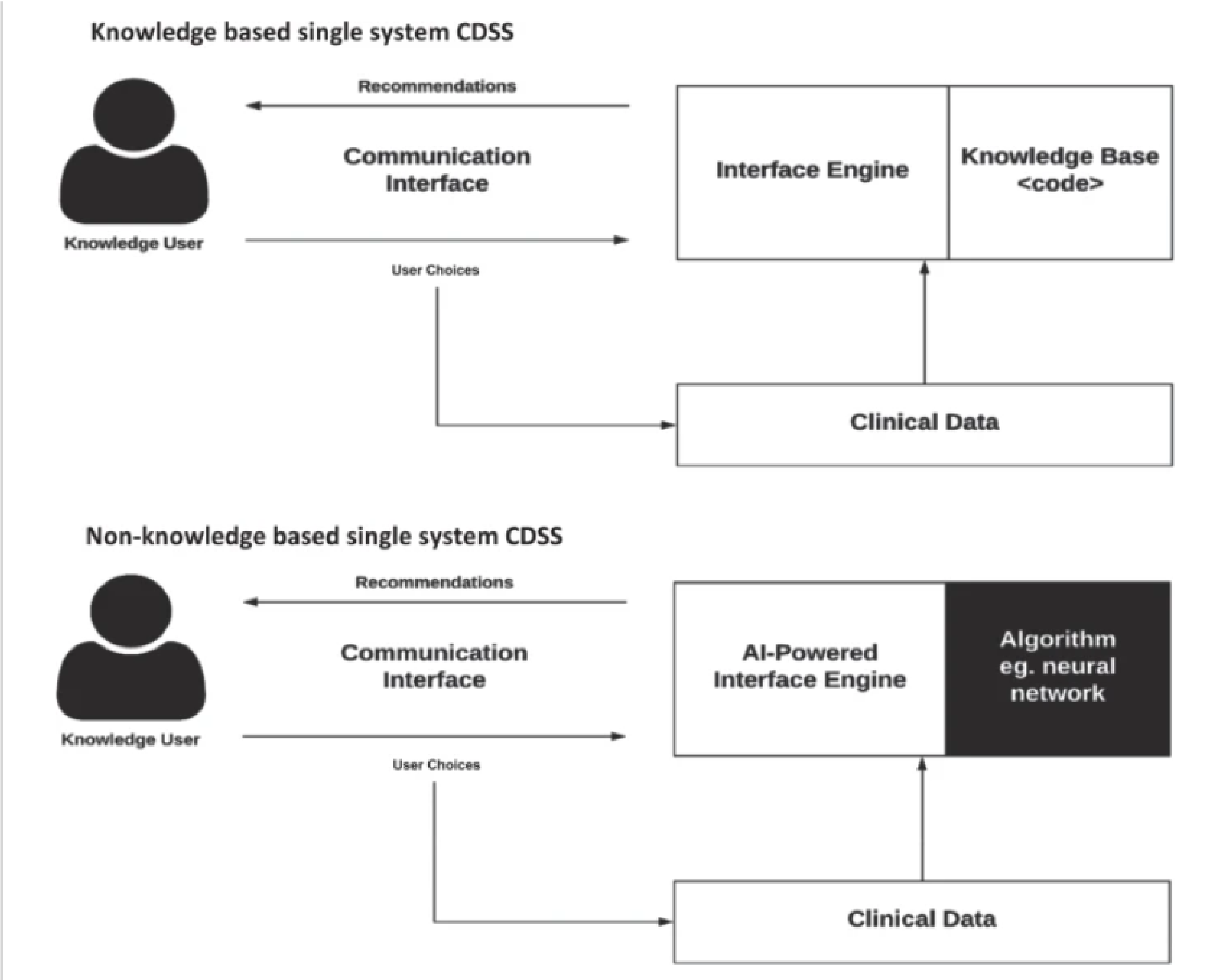
Appendices

Appendix A: Main types of CDSS



Functioning of the two main types of CDSS by Sutton et al. (2020)

Appendix B: Participant Information Sheet

PARTICIPANT INFORMATION SHEET

The title of the research project
A case study: Exploring impacts of AI use on work practices and collaborative work in healthcare

Invitation to take part
You are being invited to take part in a research project. Before you decide it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully. Ask the researcher if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part.

Why have I been chosen?
You have been selected as a potential participant because you are working in the team that has been selected as a case for this study due to its work with an AI system used to support analysis and interpretation of EEGs.

Do I have to take part?
It is up to you to decide whether or not to take part. If you do decide to take part, you will be given this information sheet to keep and be asked to sign an informed consent form. We want you to understand what participation involves, before you make a decision on whether to participate.

If you or any family member have an on-going relationship with the University of Twente (UT) or the research team, e.g., as a member of staff, as student or other service user, your decision on whether to take part (or continue to take part) will not affect this relationship in any way.

Can I change my mind about taking part?
Yes, you can stop participating in study activities at any time and without giving a reason. Read more about this in the section “Study withdrawal”.

What would taking part involve?
Study participation entails an observation session and an interview. In case potential participants don't want their work to be observed they can opt to only take part in an interview.
For the observation, the researcher is present at the hospital for some time or even the whole workday, depending on what is agreed on, to follow the professional in situations that are suited to observe their work to see what a workday looks like and how the AI usage impacts it. This of course includes observing how the AI system is directly used for diagnostic related tasks, but also other tasks and activities as it might be that the use of the AI system affects other individual or collaborative work, for example other patient care activities, administrative tasks or work meetings. Ultimately, what the researcher can observe depends on what participants feel comfortable with.
After this (if applicable), the participant attends an approximately 45 to 55 minutes long interview, to answer a number of open-ended questions about their work before and with the AI system, on a date and time convenient to the participant.

Will I be reimbursed for taking part?
No, you will not be reimbursed for taking part in the study.

What are risks of taking part?
Whilst there are no immediate benefits for those people participating in the project, it is hoped that participation will inspire you to personally think about the impact of the AI system on your work and what it allows or not allows you to do.

Whilst we don't anticipate any risks to you in taking part in this study, you may experience some discomfort during an observation session as your work is being observed by the researcher. Please know that you can voice discomfort any time and you are free to stop the session at any point.

What type of information will be sought from me and why is the collection of this information relevant for achieving the research project's objectives?
During an observation and interview session, information about your work practices and collaborative work will be collected, which involves routine and non-routine activities and actions during your workday (e.g., patient care, administrative tasks, meetings) as well as information about your role in the team, contact with and support from colleagues. This allows for making inferences about how the use of the AI system shapes your work practices and impacts collaborative work you are part of.

Will I be recorded, and how will the recorded media be used?
The audio recordings during your observation session and/or your interview will be transcribed and only used for data analysis purposes. No other use will be made of them without your written permission, and no one outside the project will be allowed access to the recording(s). The recording(s) will be deleted after transcription.

How will my information be managed?
The University of Twente is the organisation with overall responsibility for this study and the researchers are responsible for looking after your information and using it appropriately. Undertaking this research study involves collecting information that you provide. The UT manages research data strictly in accordance with:

· *Ethical requirements*; and

· *Current data protection laws (e.g., GDPR).* These control use of information about identifiable individuals, but do not apply to anonymous research data: "anonymous" means that any pieces of data or links to other data which identify a specific person as the subject or source of a research result has either been destroyed or not collected. The GDPR does however still apply to data that has been pseudonymized, as applied in this study, meaning that the unique identifier of a person is replaced with a pseudonym. This implies that the data can no longer be attributed to a specific data subject without the use of additional information which is to be kept separately and safely to ensure non-attribution. Pseudonymization is chosen to as a researcher be able to link datasets from the observation and interview to the respective individual and to be able to potentially identify differences for different roles/occupations in the team.

Research data will be used only for the purposes of the study. To safeguard your rights in relation to your (personal) information, we will control access to that data as described below.

Publication
Research results will be published a Master thesis research report which will be uploaded in the Student Theses Repository of the University of Twente (UT). The results are based on patterns and themes found in the data of participants. Moreover, the research is part of the larger SAMKIN project of the UT and therefore the data can be used for scientific publications in regards to this project.
SAMKIN project website: https://www.utwente.nl/en/bms/iebis/foe/HRM/research_hrm/SAMKIN/ .

Security and access controls
Personal information which has not been pseudonymised, which concerns the raw transcripts and field notes, will be accessed and used only by appropriate, authorised individuals and when this is necessary for the purposes of the research or for the purpose of monitoring and/or audit of the study

applied which means that only the data is collected from you which is necessary for the research purpose.

Third parties
Next to UT staff and the UT student working on the research project, your non-pseudonymized data might have to be shared with the transcription service 'Amberscript' for which the BMS faculty of the UT has a usage license.

Study withdrawal
You are free to withdraw from the study at any point in time without justification. After you decide to withdraw from the study, we will not collect any further information from or about you. If you withdraw from active participation in the study, we will delete information which we have already collected from or about you, unless you explicitly allow the further processing of the data collected before your withdrawal.

Retention of research data
The collected research data will be stored in the UT data archive for one year after completion of the research, so that we have records of how we conducted the research and to prevent loss/destruction of the data as well as to secure its authenticity. The only personal information in this document and the accompanying informed consent form will be your name and signature, and we will not link this to any research results.

Appendix C: Informed Consent Form

Consent Form

Please tick the appropriate boxes	**Yes**	**No**
Taking part in the study		
I have read and understood the study information. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	O	O
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	O	O
My participation in the study involves an observation session during which written field notes and audio recordings of myself can be taken, as well as an audio-recorded interview. The audio recordings will be transcribed and will be destroyed after this transcription.	O	O
I understand that taking part in the study involves an audio-recorded interview that will be transcribed as text. The recording will be destroyed after transcription.	O	O
I agree to be audio recorded during the interview.	O	O
I agree to be audio recorded during the observation session.	O	O
Use of the information in the study		
I understand that information I provide will be used for a Master thesis research report and Master thesis presentation. The report will be available in the UT theses repository.	O	O
As this research is part of the larger SAMKIN project of the UT, I consent that the data can be used for scientific publications in regards to this project. Project website: https://www.utwente.nl/en/bms/iebis/foe/HRM/research_hrm/SAMKIN/	O	O
I understand that personal information collected about me that can identify me [e.g., my occupation] will not be shared beyond the study team.	O	O
I understand that personal information collected about me that can identify me [e.g., my occupation] will be pseudonymised which means I cannot be identified without the use of additional information which is protected so that non-attribution is ensured.	O	O
I agree that my information can be quoted in research outputs in a pseudonymised way.	O	O
Storing of the information in the study		
I give permission for the raw and pseudonymized transcripts, as well as raw and pseudonymized field notes (if applicable), to be archived in the UT data archive for one year to prevent physical loss/destruction and to secure the data's authenticity.	O	O

Signatures

________________________ ________________________ _________

Name of participant Signature Date

I have to the best of my ability ensured that the participant understands to what they are freely consenting.

___________________________ ____________________ _________

Researcher name Signature Date

Study contact details for further information: Selina Bachem, s.bachem@student.utwente.nl

Contact Information for Questions about Your Rights as a Research Participant

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee/domain Humanities & Social Sciences of the Faculty of Behavioural, Management and Social Sciences at the University of Twente by ethicscommittee-hss@utwente.nl

Appendix D: Field notes template

Time	Activity	Place	Content	Participants	Initiative	Duration

Structure for field notes during shadowing by Askeland (2016)

Appendix E: Interview Protocol

INTERVIEW PROTOCOL

Interview questions

1. General introduction

- In general, what particular function do you occupy as a healthcare professional? (job description)
- Can you tell me a bit about the team you are part of and its overall work?
- What does the work you do look like? What are your main tasks?
- What does the care process for epilepsy look like for patients and how is your work integrated into the care process?
- How are you involved in the development of Alice?
- When is the treatment of epileptiform discharges and epilepsy itself necessary? What are the indications for when to treat EDs and epilepsy?
- When are new EEG recordings done in patients?
- What does the EEG review process look like? What are the tasks you have to do?

2. Affordances & constraints

- What do you use the AI system for? In other words, what does the AI system enable you to do?
- Specifically, which features of the system do you use?
- What parts of the PDF report do you look at/use?
- Can you use the AI on every computer?
- What does the AI system allow you to do that you were not able to do before?
- What does the AI system make easier to do?
- What does the AI system make more difficult to do?
- What are things the AI system cannot do? (Limitations of the system)
- What are other downsides of working with the AI system for you, if there are any?
- Are you afraid of using the AI system? If so, in what ways or for what purpose?
- How did you experience learning to work with the AI system? *E.g., was it easy or rather difficult for you?*
- Are there things you expected to be able to do that are not in fact possible by using the AI system? If yes, which are these?
- In your opinion, are there other things the AI system would allow you to do which you are not making use of at the moment? If so, what are these?
- If applicable, in which ways does the AI system restrict you in performing your tasks as you wish to do, or the relational component of your role? *(E.g., communication, support from and exchange of information with colleagues)*
- What do you wish the AI system would allow you to do?
- Which changes have been made to the AI system to allow for its better integration into your work?

3. Work practices

- Thinking back to ‘before’ implementation of the AI system, can you describe what a typical work day looked like for you?

- In what ways does using the AI system change your main tasks and activities? Please consider changes related to patient care and beyond
- What does a typical work day look like for you now?
- Working with the AI system, how do you feel your understanding of your tasks has changed or not? *E.g., how clearly you understand your tasks: is it more or less difficult for you to know what you have to do and how to do it*?
- How has the degree to which your job allows you to perform a *whole* piece of work and to clearly identify the outcome of your work changed or not changed? *E.g., all tasks/activities to complete your job instead of only certain tasks*
- How do you feel the quality of care has changed or not changed?
- How does working with the AI system affect or not affect the level of freedom you have in making your own decisions at work? *E.g., diagnostic decisions, decisions over all kinds of work processes*
- Does working with the AI system somehow influence to what extent you can decide when and where to work? If yes, in what ways?
- What new skills does the AI system require you to make use of, if applicable? What are examples?
- Do you feel like you still need to use the same variety of skills as before or has that changed somehow (more/less skills)? If so, in which ways? (examples)
- How has the extent to which you receive clear and direct information about the outcomes of your work and their effectiveness *from your work itself* changed or not changed?
- Could you describe to me how the 'meaning' of your work has changed, or not? *For example, how it feels your work affects others in your team or patients?*
- How do you feel as a doctor now working with the AI system?
- How does the use of the AI system change the overall diagnostic process, from your viewpoint?
- Are there other related care practices, that you know of aside from diagnostics, that are affected by use of the AI system? If so, which are these?
- Which changes do you see to occur in the future, due to the AI system, in the care practices you are involved in?

3.1 Collaborative work

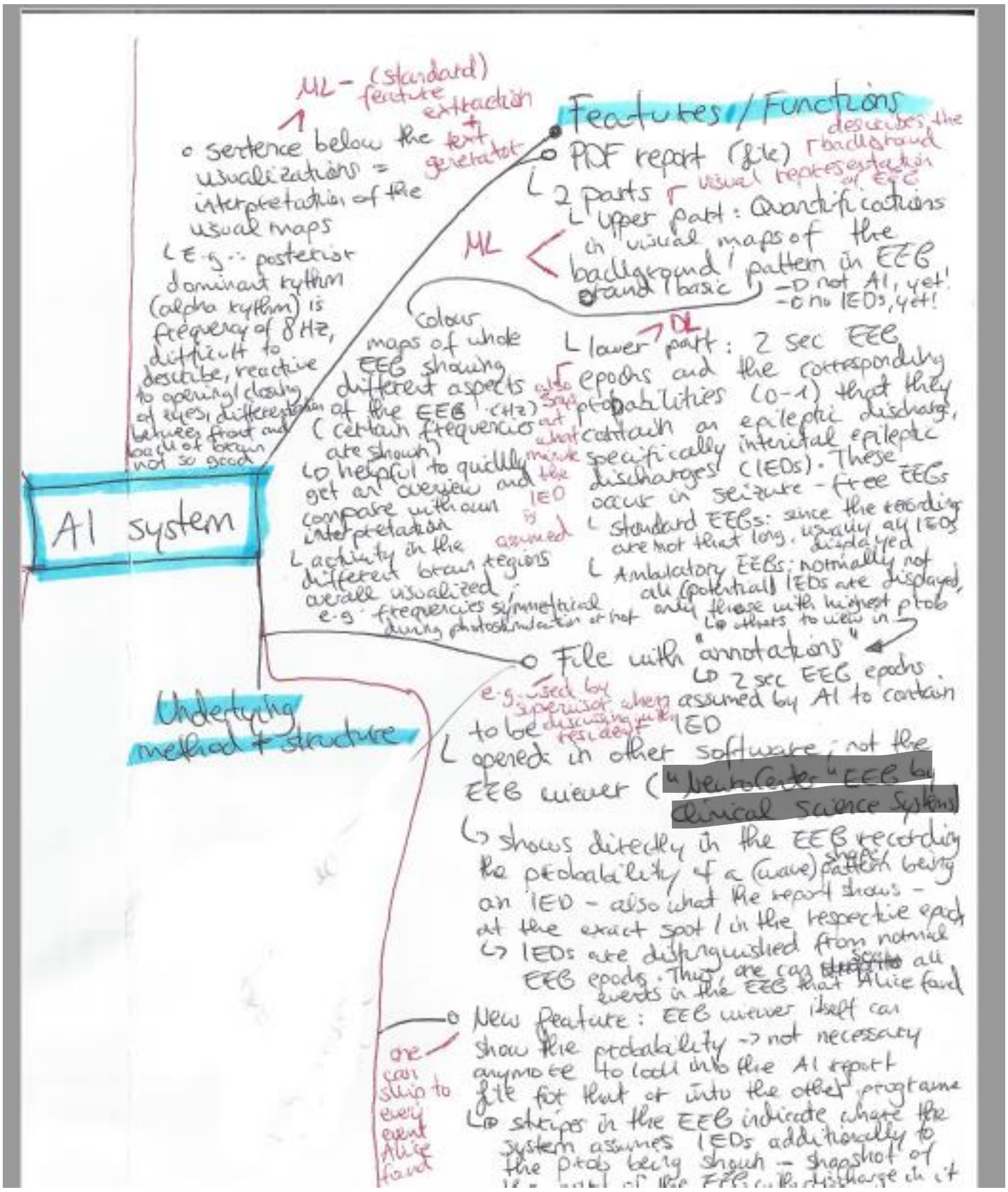
- Thinking back to 'before' implementation of the AI system, can you describe the relational component of your task?
  > That is, the 'talking to the people' which is important but may not be captured by the tasks and activities? *E.g., relationships, support from others, interacting with colleagues*
  > What did you collaborate on or interact for with colleagues during a typical workday? Can you name examples?
- How much time does collaborative work take up in relation to individual work during your workday?
- How has the relational component of your work, as described before, changed or not due to working with the AI system?
  > Is it easier or more difficult to exchange information with colleagues?
  > Have the typical interactions you have had changed?
  > Do you need more or less help with your work than before?
  > Do you collaborate more or less with others?
  > Are there changes in what you collaborate on?
  > Do you help others more or less? In what ways do you support them?
- How has the extent to which you receive clear and direct information about the outcomes of your work and their effectiveness *from others* changed or not changed?
- Working with the AI system, how has your understanding of your role in the team changed or not changed? *E.g., how clear it is to you for what you are responsible for in your team, whether you take on more or less tasks in the team than before*

4. Ending

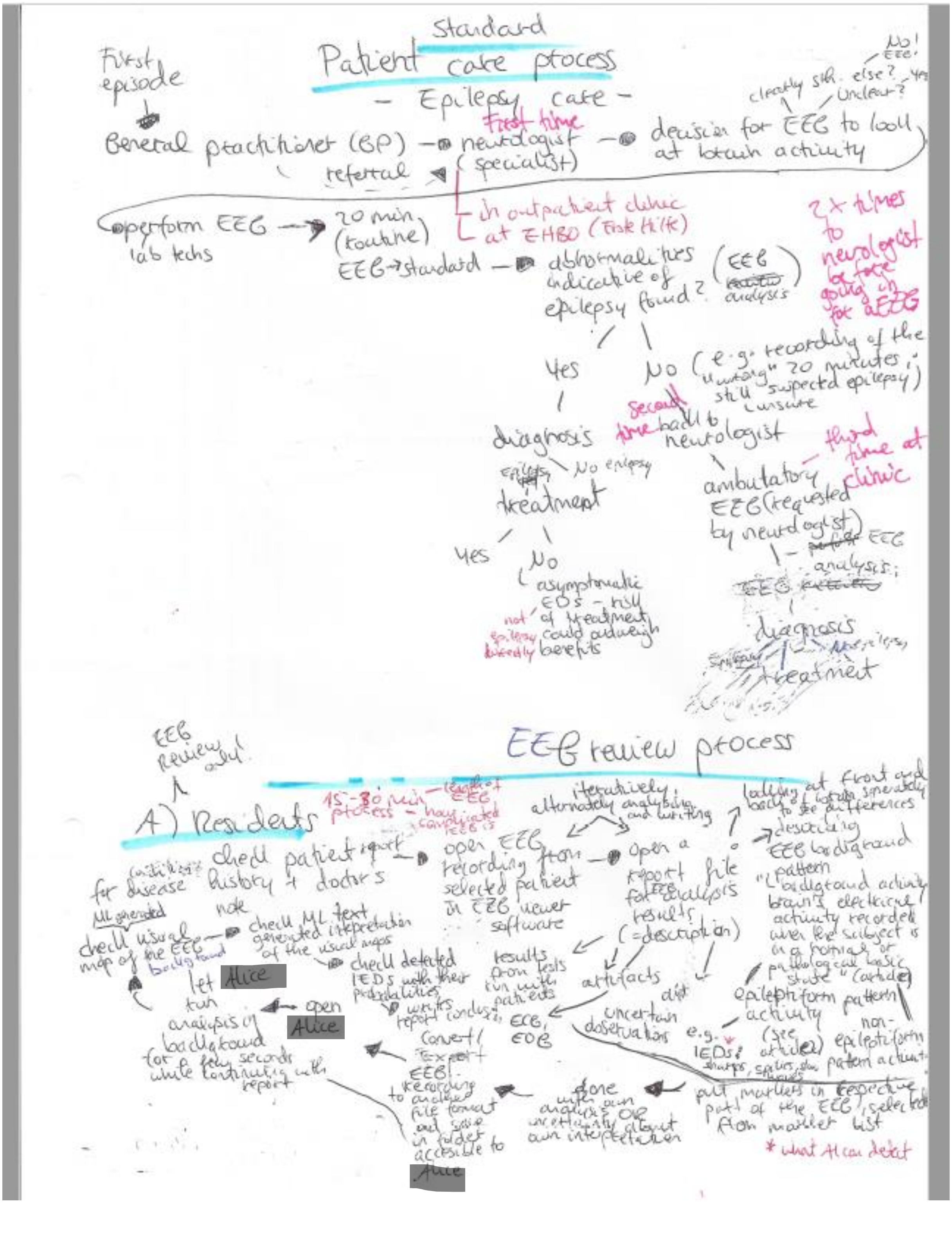
- Are there any other considerations you think are important for me/us to understand the impact of the AI system on your work or overall profession?
- ➢ Feel free to give some final remarks or ask any question you might have at this point

- ➢ Do you have protocols to which you and your colleagues stick to? *E.g. care and other work processes, AI system use*
- ➢ You can always contact me later as well in case you have a question

Appendix F: Learnings about the AI system



Appendix G: Visualizations of epilepsy care processes



Appendix H: Initial codebook

Main codes	Sub codes
Job description	Lab technician Clinical neurophysiologist Neurology resident Technical physician ICT expert
Epilepsy care pathway	Diagnosis Treatment
Work practice	Direct patient care Indirect patient care
Collaborative work	Collaborative task Responsibility in team Role in team
AI system features & functionalities	/
AI system development	Past development Future development
AI affordance	Shared affordance Collective affordance Individualized affordance
AI constraint	/

Work characteristic	Job autonomy & control
	Job feedback
	   > Role clarity
	Skill variety & use
	   > Task significance
	   > Task identity
	Social & relational elements
	   > Support
	   > Relationship
	Job demands

AI use impact on work	Augmentation Automation Actuation Assistance Splitting up Relieving Replacing

Appendix I: Code of Conduct

STUDENT CODE OF CONDUCT FOR PARTICIPATION IN SHADOWING

When shadowing a healthcare professional, I will:

1. Arrive promptly.

2. Accurately represent my position and role.

3. Appreciate the limits of my role as an observer by not engaging in activities and tasks generally reserved for the trained health professional.

4. Respects patients' rights to refuse to have students present.

5. Treat all patients and staff with respect and dignity, regardless of age, gender, race, ethnicity, national origin, religion, disability, or sexual orientation.

6. Maintain strict confidentiality and privacy about patient information.

7. Maintain honesty and integrity by being forthright in my interactions with patients and staff.

8. Ensure patient safety by remaining at home if I am ill; and will notify professional of my planned absence.

9. Behave in an appropriate, professional, courteous manner at all times.

10. Not initiate or accept patients' invitations to engage in social or social media relationships.

11. Dress and act professionally.

12. Not abuse drugs or alcohol.

13. Be aware of and follow the guidelines of the setting in which I am an observer.

I agree to follow the Code of Conduct described above:

Signature: Selina Bachem

Print name: Selina Bachem

Date: 01.04.2023

AAMC (2013). *Guidelines for Clinical Shadowing Experiences for Pre-medical Students.* Retrieved March 25, 2023, from https://www.aamc.org/media/23341/download

Appendix J: Confidentiality statement

<u>CONFIDENTIALITY STATEMENT OF PATIENT INFORMATION</u>

In the Netherlands, patients have a right to confidentiality and privacy related to their medical treatment, as laid out in the Dutch Civil Code (CDC).

Confidential Patient Information includes*:*
Any individually identifiable information in possession or derived from a provider of health care regarding a patient's medical history, mental or physical condition or treatment, as well as the patients and/or their family members records, test results, conversations, research records and financial information. Examples include but are not limited to: physical medical records including paper, photo, video, diagnostic and therapeutic reports, laboratory and pathology samples; patient insurance and billing records; computerized patient data; visual observation of patients receive medical care or accessing services; and verbal information provided by or about a patient.

I understand and agree that this document establishes a Confidentiality Agreement between me

Selina Bachem, a student at University of Twente

and

Medisch Spectrum Twente (MST)

and sets forth the understanding regarding the protection of any confidential information that the student may have access to while doing research at the neurology department with the following purpose: Conducting shadowing sessions with healthcare professionals from the neurology department for Master thesis research

1. I understand that I will become acquainted with the following information relating to MST patients: clinical/medical information, visual observation of patients receiving medical care or accessing services. It is understood and agreed that I will use and hold all Information in strict trust and confidence and will use such information only for the purposes contemplated herein, and not for any other purpose.
2. I acknowledge that it is my responsibility to respect the privacy and confidentiality of information received from MST. I will not access, use or disclose patient or other confidential information, I further understand that I am required to immediately report any information about unauthorized access, use or disclosure of confidential patient information to MST.
3. I agree to not disclose the Information to any other individuals.
4. I understand and acknowledge that, should I breach any provision of this Confidentiality Statement, I may be subject to civil or criminal liability.

Signature: Selina Bachem
Date: 01.04.2023

Print Name: Selina Bachem
Email: s.bachem@student.utwente.nl

World Templates Online (2023). *16 Basic Confidentiality Statement Examples [Free Templates]*. Retrieved March, 26, 2023, from https://www.wordtemplatesonline.net/basic-confidentiality-statement-examples/

Appendix K: Other work of healthcare professionals in the team
In total, two to three clinical neurophysiologists as well as residents, one to three researchers and six to seven laboratory technicians are part of the team.

Lab technicians:

- Electromyography (EMG): During an EMG, function of nerves and skeletal muscles are evaluated by electrical stimulation and recording (Ibrahim et al., 2015).
- Ultrasound of the carotid arteries: This is done for an assessment of stenosis.
- Duplex sonography: A noninvasive method to examine blood vessels by use of ultrasonic waves.
- Videonystagmography (VNG): During a VNG the patient's eye movements are recorded and analyzed to assess whether a vestibular disease causes the patient's problems with dizziness or balance (Mekki, 2014).
- Somatosensory Evoked Potential tests: During these tests the nervous system's neural activity is measured through setting somatosensory stimuli (Fustes et al., 2021).
- Sleep study: The purpose of a sleep study, also referred to as polysomnography, is to diagnose sleep-related disorders (Mayo Clinic, 2023b).

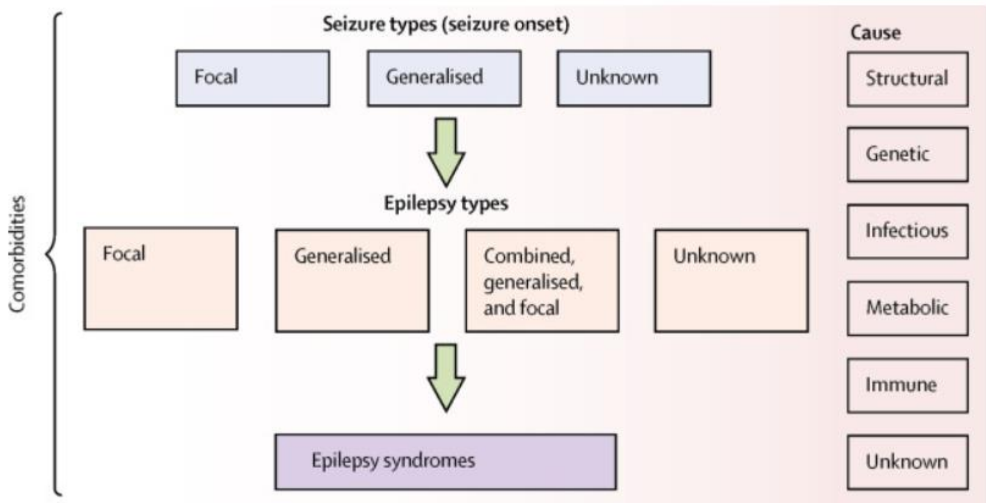
Further, lab technicians not only work in the neurology department but also work on the emergency department to conduct tests and to monitor patients on the ICU by measuring long-term EEGs, for example after cardiac arrest, and intraoperatively in the OR. In addition, some of them are involved in research activities and are supporting students during their studies.

Neurophysiologists:

- Seeing ambulatory patients in the outpatient clinic for disorders of consciousness such as epilepsy
- Guiding diagnosis and therapy for ICU patients with primary and secondary neurological problems in collaboration with intensivists
- Teaching and supervising neurology residents and technicians in training as well as assisting them during neurological tests such as EMGs
- Leading or partaking in research projects and supporting students in their studies

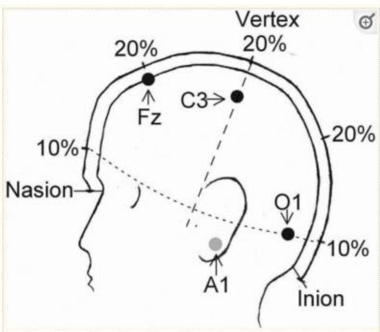
Appendix L: Framework for epilepsy classification
Epilepsy is classified at three levels which are type of seizure, epilepsy type and epilepsy syndrome, developed by the International League Against Epilepsy and reproduced by Thijs et al. (2019) as adopted here. Seizures are classified as focal when they seem to occur due to abnormal electrical activity in one area of the brain, whereas generalised seizures are caused by activity in apparently all brain areas (Mayo Clinic, 2023a). Multiple sub-types for these main seizure types exist which are associated with various symptoms and manifestations, making it difficult to demarcate them from other disorders and therefore requiring extensive examination (Mayo Clinic, 2023a). Additionally, important to note is that experiencing a

seizure does not necessarily mean that the person has epilepsy (Mayo Clinic, 2023a). Epilepsy is diagnosed only under specific conditions. The most precise diagnosis is made when an epilepsy syndrome is diagnosed (Thijs et al., 2019), which is determined by the bundle of clinical features such as seizure type(s), comorbidity, age of seizure onset and EEG findings as well as potential brain imaging results of a patient (Thijs et al., 2019; Gerard & Samuels, 2017). Further, epilepsy is also diagnosed when two unprovoked seizures occurred that were more than 24 hours apart or when one unprovoked seizure took place which has a recurrence risk of more than 60 percent for the upcoming ten years (Thijs et al., 2019). In general, four types of epilepsy are defined, as seen in Figure 1, with *combined generalised and focal epilepsy* being a new category to describe cases in which both seizure types appear (Thijs et al., 2019). Unfortunately, a number of epilepsy cases cannot be traced back to a certain cause and cannot be clearly classified, leading to a less specific diagnosis (Neligan et al., 2012; Thijs et al., 2019).



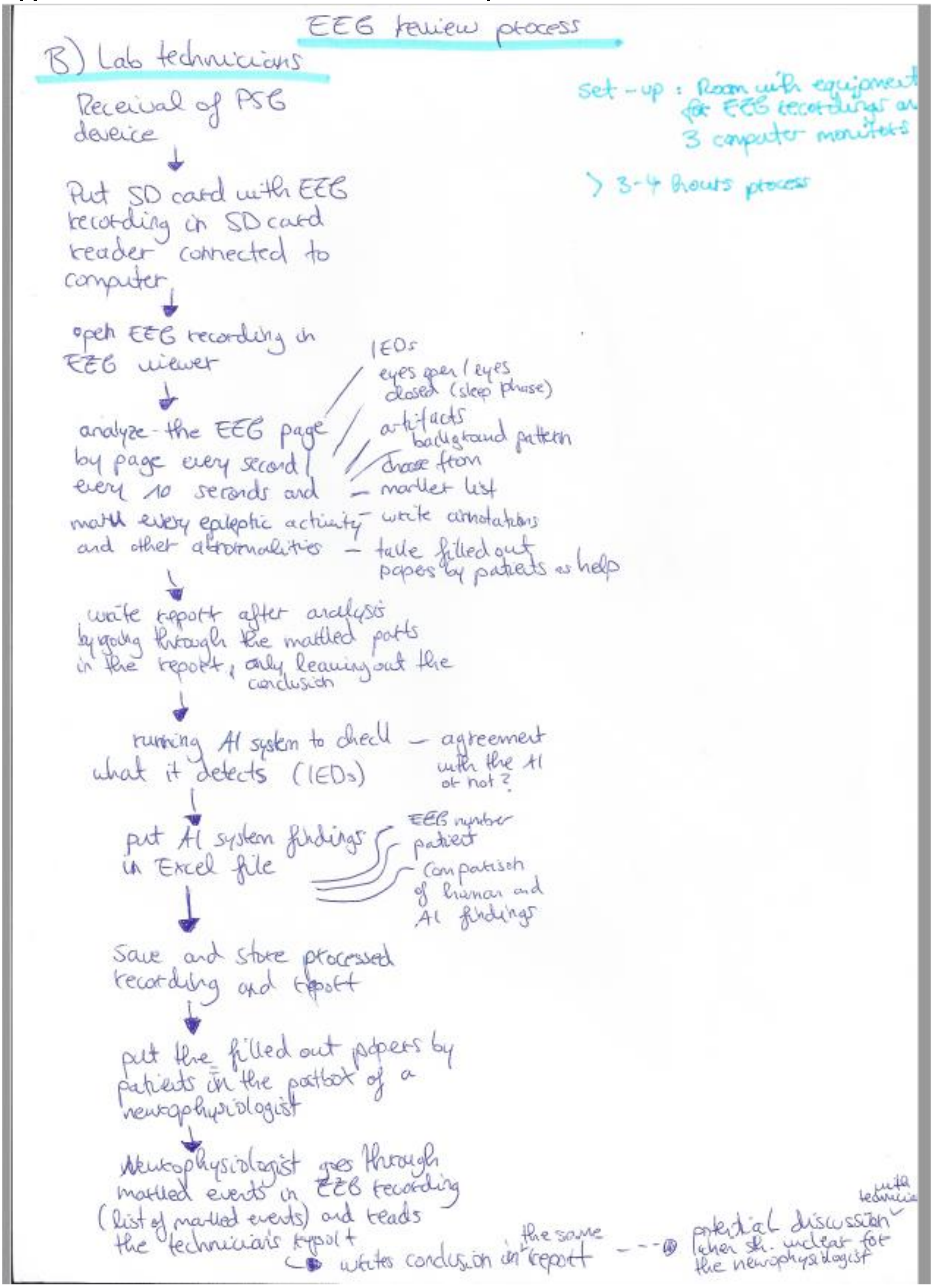
Thijs et al. (2019)

Appendix M: 10-20 electrode placement system



The figure displays the electrode placement according to the 10-20 system, adopted from Campbell (2009) based on Jasper (1958). The system works as follows: “The longitudinal line from the nasion to inion is divided into 10% and 20% segments. Distances along the transverse line (dashed) and the circumference (dotted) are not to scale because the 3-dimensional head is drawn in 2-dimensional profile. Approximate locations of Fz, C3, O1, and A1 (behind the ear) are indicated.” (Campbell, 2009, p. 16).

Appendix N: Visualizations of the EEG review process



EEG review / analysis + interpretation process

AI nice to have as it helps

Policy:

Both always to be reviewed by professional

AI really necessary → reduces the amount to look at in an EEG recording (e.g. instead of looking at 24h, look at 3 min. of flagged epochs

Standard EEG (20 min.)

- first time EEG ①
- subsequent EEG for comparison ②
  - 45 min with patient preparation

Lab technicians perform them

Residents together with their supervisor (neurophysiologist) analyse and interpret them. Resident analysis: 15 to 30 min worth, usually 20

look at report + EEG again together, sometimes supervisor looks in Alice

Lab technicians make annotations during EEG recording about when (external) stimuli are set (e.g. light test) or where they assume abnormalities / atypicalities (hyperventilation, speaking during)

(e.g. rhythm going too slowly (Hz), looks asymmetrical, slower activity in frontal regions and left side of brain due to problems with speaking / also where eyes are open / closed which patients are instructed to do during recording

Aim of analysis: Write report that can be discussed with supervisor

Reporting of ECG (heart rhythm) also necessary → can lead to artifacts in the EEG

- rhythm of the heart exactly the same as in EEG?
- heart rhythm problems?
- is recorded at the same time as the EEG

outpatients EEGs: Photostimulation is always done, meaning that light pulses at certain frequencies between 4 to 20 Hz are used on the patient for stimulation with a flashlight

- in EEG viewer: every green stripe = burst of light
- response of the brain is observed - it goes with the same frequency as the stimuli which is expected to see because that's normal. However the reaction can also be different (which is also ok to an extent), e.g. stimuli is 2, brain waves are at 4 Hz, 5 → 10, 10 → 15, 4 → 8, 12 → 16 → ? also expected reaction of the brain to the lights
- abnormal when problems with the eyes, e.g. cannot see → brain continues on own pace
- also abnormal when asymmetrical, so less clear reaction on one side of the brain, e.g. when it's damaged
- can provoke epileptic seizures in certain kinds of epilepsy → main reason for doing it, esp. in children it happens that epileptic discharges are only occurring during this stimulation

first: description of ground pattern, using lab tech's annotations as guidance

second: looking at each page in the recording to look for abnormalities and other events to discuss with supervisor - makes note for everything considered worthy of attention → also potential indicators for diseases / health conditions other than epilepsy ~~that~~

Ambulatory EEG (24 h)

- when standard EEG unclear - unsure about diagnosis
  - higher sensitivity than with standard EEG
  - chance of finding abnormalities (discharges) etc. is ~~higher~~ larger in a patient with epilepsy → mainstay of diagnosis
- specific reasons (article "Indications and yield of ambulatory EEG recordings"):
  - detection of IEDs
  - capturing + characterising clinical events
  - detecting unrecognized seizures
  - monitoring IEDs during treatment
- IEDs especially occur during sleep → EEG measurements also / only take place in night