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# AI AND HEALTHCARE SYSTEMS: TECHNOLOGICAL FOUNDATIONS AND SOCIETAL IMPLICATIONS

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## Abstract

This thesis explores the transformative role of Artificial Intelligence (AI) in healthcare, focusing on its technological foundations, medical applications, and ethical challenges. After an introduction on the tecnologies used, it examines AI role in early diagnosis and prevention, particularly for dementia and Alzheimer's disease, highlighting the potential for improved accuracy and cost savings. Additionally, the study addresses critical ethical considerations, such as data privacy and algorithmic fairness. By combining technical analysis and practical insights, this thesis highlights AI's transformative potential in healthcare while addressing the need for ethical integration and further implementation.

## Keywords

Artificial Intelligence in Healthcare | Early Diagnosis and Prevention | Healthcare Spending | Ethical Challenges in AI

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# 1. Introduction

Artificial Intelligence (AI) is commonly defined as "machine's capacity to carry out operations that ordinarily require human intellect, such as speech recognition, understanding of natural language, and decision-making" (Soori et al. 2023), and since its first applications in technology, it has been a crucial tool in human development (Ali et al. 2023). AI further integration in healthcare marks another transformative step towards new opportunities to revolutionize the industry.

The first ever application of AI in healthcare system, can be tracked back in the 1970s, when, in form of expert systems, it was used to encode clinicians' diagnostic reasoning into computer programming (Arefin 2024). Afterwards, in the 1990s, neural networks started to be applied to problems such as categorizing cell images and detecting patterns in patients' records, due the higher availability of larger datasets and computing power (Arefin 2024). Since then, AI rapidly spread throughout healthcare systems, from disease detection to drug discovery.

Different models are used for the application of AI in healthcare, Natural Language Processing (NLP) and Machine Learning (ML) are the most used regarding unstructured health data from diverse sources, while Deep Learning (DL) is leading the evolution of AI towards personalized predictive models (Soori et al. 2023). Advancements in Machine Learning, Deep Learning and Natural Language Processing, will enable AI to enhance many aspects of healthcare, ranging from diagnostics and treatment planning to patient monitoring and administrative efficiencies.

As healthcare systems are globally facing increasing demand alongside constrained resources, AI is a promising tool to address longstanding challenges, such as diagnostic errors, optimization of treatment protocols and improvement of overall system efficiency (Bajwa et al. 2021). Furthermore, it has the potential to streamline workflows, reduce healthcare costs and provide access to quality care in under-resourced settings.

However, the application of AI involves significant challenges: for instance, ethical considerations, data privacy and security concerns, alongside the critical need for human oversight in clinical decision-making, present substantial obstacles (Mennella et al. 2024). These challenges underscore the importance of developing frameworks and standards that ensure AI is used responsibly and transparently.

Regardless, looking ahead, the continue evolution of AI and the advancement in technology offers promise of a more efficient, predictive and personalized healthcare system. It holds the potential to reshape how illnesses are diagnosed, treated and managed, leading to a landscape where care is also anticipatory and tailored on individual needs. In navigating the balance between innovation and ethical responsibility, the future of AI in healthcare could ultimately redefine the boundaries of medical science and patient care.

This thesis examines the general application of AI in healthcare, including its impact on dementia and Alzheimer's disease. Despite their broad occurrence, these illnesses provide substantial diagnostic problems, and there is currently no cure. These reasons underline the importance of AI as a transformative tool, with the potential for earlier diagnosis, improved diagnostic precision, and more targeted treatment techniques. With a focus on its applications in the diagnosis and treatment of specific diseases, this thesis provides a thorough analysis of artificial intelligence's place in contemporary healthcare systems. This paper aims to examine these topics and offer an in-depth overview over the technologies used, the ethical issues involved, the costs, and the overall AI adoption in healthcare.

# 2. AI in Healthcare

## 2.1 Technology, Economics and Ethics

AI is revolutionizing the healthcare landscape, addressing critical challenges while enhancing opportunities for efficiency, cost-effectiveness and improved patient care. As healthcare systems aim to achieve the "quadruple aim" of improving population health, patient experiences, caregiver satisfaction, and reducing costs (Arnetz et al. 2020), AI emerges as a transformative force. However, the adoption of AI is not without complexities, including technological, financial, and ethical considerations that must be carefully managed (Bajwa et al. 2021). This chapter explores AI's role in healthcare from three perspectives: the technological foundations of AI, its implications for healthcare spending and cost optimization, and the ethical challenges and responsibilities accompanying its integration. By providing a comprehensive analysis, the chapter sets the stage for understanding how AI can both address pressing healthcare issues and shape the future of medical practices responsibly.

## 2.2 Technological Foundations of AI in Healthcare

Healthcare systems are facing significant challenges in achieving the so-called "quadruple aim", which consists in reducing costs, improving population health, patient experience and team well-being (Arnetz et al. 2020), and AI has emerged as a promising solution to address these challenges by offering tools that enhance efficiency, improve diagnostic accuracy, and potentially lower healthcare costs. This chapter provides an overview of AI exploring its fundamental components, capabilities, and applications within healthcare.

AI is a branch of computer science focused on creating machines and algorithms capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and pattern recognition (Soori et al. 2023). Through a combination of data-driven algorithms and computational power, AI systems can process and interpret vast amounts of information, recognize patterns within complex datasets, and make informed decisions. At its core, AI's strength lies in its ability to learn and improve over time, especially when applied to large, multidimensional datasets that are often encountered in the healthcare sector. (Tsoi et al. 2022; Bohr et al. 2020).  AI is an umbrella term that encompasses various subfields, each contributing unique methods and capabilities. The most prominent for healthcare include Machine Learning (ML), Natural language Processing Learning (NPL), Deep Learning (DL), and Reinforcement Learning (RL), each of which plays a role in advancing AI's effectiveness in healthcare applications (Bajwa et al. 2021). Before discussing AI's applications in healthcare, it is essential to understand the basic subfields and methodologies that underpin AI.

Machine Learning (ML) refers to the study of algorithms that allow computer programs to automatically improve through experience (Mhlanga et al. 2023). It can be divided between three types according to whether the input data are labeled. *Supervised learning* means training a model on a dataset annotated with labels applied in classification and regression tasks, in healthcare it applies for example in medical imaging analysis (Arefin 2024). *Unsupervised models* learn from unlabeled data by extracting features and patterns in solving clustering problems (Tsoi et al. 2023). *Semi-supervised* method builds a model on a training dataset with labels on one part and no labels on the other (IBM 2023). In healthcare the most common application of traditional machine learning is precision medicine, which requires a training dataset for which the outcome variable is known (Davenport et al. 2019). A more complex form of machine learning is neural network. It refers to algorithms inspired by the human brain's structure. They consist of interconnected layers of "neurons" that allow the model to learn from data in a more nuanced way. Neural networks are the foundation of deep learning, enabling AI systems to process highly complex data, such as medical images or genomic sequences (Zhang et al. 2023).

Reinforcement Learning (RL) refers to "computational autonomous agents that learn by trial and error or by expert demonstration without any guidance from humans" (IBM 2024). Reinforcement learning frameworks and methods are broadly applicable to clinical settings in which decisions are made sequentially, for instance, treatment recommendation. (Khezeli et al. 2023).

Natural Language Processing (NLP) allows to understand, generate and process human language (IBM 2024). There are three different approaches to Natural Language Processing: rules-based NLP, statistical NLP and Deep Learning NLP. In healthcare, NLP is used to power chatbots for symptomatic assessment and virtual assistants for administrative tasks (Arfin

2024), indeed, this model is especially useful for automatic tasks, such as customer support or data entry (IBM 2024).

Deep Learning (DL) is a subset of ML that uses multi-layered neural networks to process and learn from large datasets (Holdsworth et al. 2024). This model can be used in healthcare to help reduce care costs, the administrative load of healthcare professionals and prevent delays in reporting urgent cases (Javaid et al. 2022).

To have a further understanding of the models, *Table 1* provides an overview of how they relate to healthcare and machine learning, which is the broadest category of AI focused on learning from data.

*Table 1 Machine Learning, Deep Learning, Natural Language Processing, Reinforcement Learning*

| Activity | Definition | Relation to ML | Healthcare Applications |
|---|---|---|---|
| **Machine Learning (ML)** | Teaching computers to learn patterns and make decisionswithout explicit programming | The broadest category; includes DL,RL, and more | General data-driven approaches for diagnostics, patient risk prediction and resource management |
| **Deep Learning (DL)** | A type of ML using neural networks with multiple layers for advanced pattern recognition | Subfield of ML, specialized for handling big data and complex problems | Advanced image and signal analysis, drug discovery and personalised medicine |
| **Natural Language Processing (NLP)** | A field combining ML/DL techniques to process and understand human language | Often uses DL for modern tasks but can also rely on simpler ML methods | Processing clinical notes, summarising medical literature or enabling chatbots for patient support |
| **Reinforcement Learning (RL)** | A method in ML where a system learns by trial and error in an interactive environment | A distinct approach within ML, not directly tied to DL or NLP | Optimising treatment strategies, robotic strategies or adaptive care pathways |

Research in AI applications for healthcare is rapidly advancing, with promising use cases emerging across various areas, including drug discovery, virtual clinical consultations, disease diagnosis, prognosis, medication management, and health monitoring. Furthermore, AI has the potential to help healthcare systems achieve the "quadruple aim" by enhancing precision in diagnostics, therapeutics, and personalized medicine (Arnetz et al. 2020). Indeed, AI's versatility supports a wide range of healthcare applications, from diagnostic and treatment solutions to patient engagement and adherence, as well as administrative functions. By automating and optimizing these processes, AI can improve healthcare efficiency, support clinical decision-making, and ultimately contribute to better patient outcomes and reduced costs. In *Table 2* is possible to have an overview regarding how AI applications would solve the quadruple aim of healthcare.

*Table 2 Healthcare Quadruple Aim and AI Applications*

| Quadruple Aim | AI Applications |
|---|---|
| **Improved Patient Experience** | Precision diagnostics, Virtual consultations |
| **Enhanced Population Health** | Disease surveillance, Health monitoring |
| **Reduced Costs** | Drug discovery, Medication management |
| **Improved Provider Satisfaction** | Administrative support, decision-making tools |

## 2.3 AI and Healthcare Spending

AI is expected to significantly influence healthcare spending, with its applications potentially driving down costs in various areas of the healthcare system. To understand the extend of these changes, this section focuses on the healthcare system in the United States, which, besides being the leading nation in the industry in terms of medical training, research and technology (Khanna et al. 2022) it has the lowest health results and public services when compared to the top ten nations. Indeed, high healthcare costs in the U.S. have become a substantial burden, making it difficult for many Americans to afford essential health services. Furthermore, between 1960 and 2022 healthcare spending in the United States increased drastically, from 5.0 to 17.9 percent of GDP, which is an average increase of USD 146 to USD 10,739 per person (Khanna et al. 2022). AI has the potential to reduce costs across multiple domains within healthcare, including administrative expenses (which account for roughly 25% of U.S. healthcare spending), patient care management, clinical operations, and diagnostics. According to research, implementing AI technologies could save between 5 and 10 percent of total healthcare spending in the United States over the next five years (Sahni et al. 2023).

To assess how these savings can be achieved, the healthcare sector can be divided into five key stakeholder groups: hospitals, physician groups, private payers, public payers, and other care providers, such as dentists (Sahni et al. 2023). Notably, hospitals, physician groups, and private payers alone generate around 80% of the industry’s total revenue. By analyzing each group’s core functions, we can estimate the potential net savings AI could generate. “Net savings” here refers to the total gross savings from AI adoption, minus the ongoing expenses required to operate AI systems (Sahni et al. 2023).

### 2.3.1 Hospitals

In hospitals, AI is applied across nine key domains: continuity of care, network and market insights, clinical operations, clinical analytics, quality and safety, value-based care, reimbursement, corporate functions, and consumer interactions (Sahni et al. 2023). For example, during the COVID-19 pandemic, many hospitals were overwhelmed by patient inquiries and lacked the necessary staff to manage the surge in calls. AI, specifically Natural Language Processing (NLP), played a crucial role in addressing this issue. NLP-based virtual agents were deployed to handle incoming calls, directing patients to appropriate resources and reducing the burden on hospital staff. Hospitals are indeed highly motivated into adopting AI because of their individual incentives to reduce operational costs and improve patient outcomes and therefore also reducing medical errors.

As of 2019, the total spending for hospitals was approximately $1,096 billion, with 80% allocated to medical services and 20% to administrative costs. AI adoption in hospitals could yield substantial savings of $60 billion to $120 billion over the next five years, without compromising the quality or accessibility of healthcare services (Sahni et al. 2023).

### 2.3.2 Physician Groups

Physician Groups are also adopting AI in the same nine functional domains as hospitals. These groups are particularly focused on reducing missed appointments and ensuring patient access to medical providers by optimizing their operations and improving access deployment. Quality and safety measures are also a priority, as they directly influence financial outcomes.

However, AI adoption within these domains varies. Clinical operations, which are critical to the financial stability of physician groups, are more advanced in AI implementation, while continuity of care remains underdeveloped due to fragmented data. Application Programming Interfaces (APIs) are a set of rules or protocols that enables software applications to communicate with each other to exchange data, features and functionality (IBM 2024), and are increasingly used to facilitate data sharing, helping overcome these limitations.

Physician groups have annual costs of around $711 billion, with 70% attributed to medical care and 30% to administration. By integrating AI technologies, physician groups could save up to $60 billion over the next five years (Sahni et al. 2023).

### 2.3.3 Private Payers

Private Payers, such as insurance companies, utilize AI across six primary domains: healthcare management, provider relationship management, claims management, member services, corporate functions, and marketing and sales. In healthcare management, AI has proven especially valuable for care coordination, managing clinical utilization, and monitoring spending. One notable application of AI among private payers is predictive modeling for behavioral health needs, which helps connect patients with appropriate support resources. For instance, one machine learning model was implemented to lower readmission rates among high-risk patients. Results were impressive: 70% more members engaged with their care managers, follow-up visits with primary care physicians increased by about 40% within 30 days of discharge, and the all-cause readmission rate dropped by 55% for the targeted group.

In 2019, private payers' total expenditures were about $1,135 billion, with 85% allocated to medical costs and 15% to administrative functions. AI could potentially reduce these costs by up to $110 billion over the next five years (Sahni et al. 2023).

Combining the savings from hospitals, physician groups, and private payers, AI could lead to an overall reduction of $200 to $360 billion in healthcare spending over the next five years.

This would equate to a 5% to 10% reduction in total U.S. healthcare costs, a significant financial impact that could make healthcare more affordable and accessible for Americans (Sahni et al. 2023).

## 2.4 Challenges and Ethical Considerations of AI

The application of Artificial Intelligence in healthcare has led to transformative advancements, offering significant benefits across various domains, such as early diagnosis, preventive care and cost optimization. However, alongside these promising innovations there are challenges and ethical considerations that demand careful examination. This chapter will delve into the complex interplay between the advantages of AI in healthcare and the ethical and practical dilemmas it introduces, shedding light on the critical issues that shape its responsible and equitable integration into the industry. Let’s begin by exploring the foundational ethical principles that guide healthcare practice, serving as moral compasses for professionals in their interactions with patients, colleagues, and society (Harishbhai Tilala et al. 2024). Beneficence emphasizes the duty to act in the best interests of patients, focusing on promoting well-being and improving health outcomes. Complementing this, non-maleficence highlights the obligation to avoid harm, encouraging healthcare providers to exercise caution and prudence in clinical decision-making to safeguard patient safety. Autonomy underscores the importance of respecting patients’ rights to make informed decisions about their care, recognizing their capacity for self-determination and honoring their personal agency. Finally, justice advocates for the equitable distribution of healthcare resources, ensuring fair access to high-quality care regardless of socioeconomic or demographic factors (Varkey 2021; Harishbhai Tilala et al. 2024). Together, these principles uphold the ethical foundation of compassionate, safe, respectful, and fair healthcare.

### 2.4.1 Ethical Challenges of AI in Healthcare

The application of AI in healthcare rises ethical concerns that must be addressed, and we can divide them in four major ethical issues: safety and transparency, algorithmic fairness and biases, clinical validation and regulation, privacy and data security (Naik et al. 2022).

#### *2.4.1.1 Privacy and Data Security*

Protecting patient privacy and sensitive medical data is a crucial factor to consider when implementing AI and machine learning in healthcare. Indeed, to function effectively, AI devices must gather a significant quantity of data, which may compromise patient privacy: this issue extends beyond data leaks and involves the utilization of private clinical data. To reduce exposure to sensitive patient data and safeguard sensitive data from privacy issues associated with AI and ML applications, data minimization and anonymization techniques must be prioritized (Harishbhai Tilala et al. 2024). Furthermore, as new technologies emerge, they must be adopted in accordance with the resulting ethical norms and privacy legislation. Is therefore crucial to align the new privacy regulations with the already existing governmental regulation, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States, which establishes federal standards protecting sensitive health information from disclosure without patient's consent (U.S. Centre for Disease Control and Prevention 2024), and the General Data Protection Regulation (GDPR) in the European Union (Amini Mohammad et al. 2023). In another front, the European Parliament's resolution, based on research by the policy department for "Citizens' Rights and Constitutional Affairs," emphasizes the urgent need for a legislative framework to govern robots and AI. The goal is to address ethical and legal concerns in areas like healthcare while anticipating scientific advancements to ensure adaptability and relevance over time (Naik et al. 2022).

#### 2.4.1.2 Algorithmic Fairness and Biases

The problem of algorithmic bias and its effects on fairness and equity in healthcare delivery are important factors that need to be considered. AI and ML algorithms are indeed highly sensitive to bias and if left unaddressed it can lead to the disruption of the principles of fairness, justice and equity in healthcare, perpetuating discrimination and reinforcing existing disparities and hindering efforts to achieve health equity (Naik et al. 2022).

To prevent the bias, there are few things that need to be implemented in the healthcare organizations systems. First, datasets need to be inclusive of diverse patient populations and account for demographic, socioeconomic and cultural factors. Ensuring inclusivity is crucial because AI systems trained on non-representative datasets may perform poorly for underrepresented groups (Harishbhai Tilala et al. 2024). Furthermore, is important to mitigate biases in AI and ML models through algorithmic fairness techniques, such as fairness-aware training algorithms, post-processing methods. Additionally, algorithmic bias can be further explained and identified through transparent and interpretable ML techniques. To ensure that algorithmic results remain fair and equitable over time, regular audit and evaluations of AI and ML algorithms are also essentials to monitor bias-induced disparities, therefore healthcare organizations should establish mechanisms for ongoing monitoring and evaluation of AI and ML applications (Harishbhai Tilala et al. 2024).

#### 2.4.1.3 Safety and Transparency

Safety and transparency are crucial concepts to foster trust and accountability: the lack of transparency can only enhance skepticism towards AI-driven healthcare technologies and therefore hindering their acceptance and use in clinical practice. Transparency refers to the openness and accessibility of information regarding the functioning and decision-making processes of AI and ML algorithms (Harishbhai Tilala et al. 2024). To foster transparency, healthcare organizations need to provide algorithmic transparency reports that document the development, validation and performance of AI and ML models in a clear and accessible manner. By doing so, healthcare organizations can instill trust and confidence in the reliability and validity of algorithmic outputs and have a clear explanation of AI language: this will ensure that AI language is accessible also to non-experts and therefore allow to make informed decisions about patient care (Harishbhai Tilala et al. 2024).

#### *2.4.1.4 Clinical Validation and Regulation*

The adoption of AI and ML technologies, requires the application of robust clinical validation and regulations to ensure the patient’s safety and efficacy. Validation and regulation are crucial to deliver accurate, reliable and clinically relevant results, therefore there is the pressing need to standardize frameworks and methodologies to validate AI and ML algorithms in healthcare settings. Furthermore, it is important to include validation studies to involve diverse patient populations and real-world clinical scenario to ensure the generalizability and scalability of AI driven technologies across different healthcare settings and patient demographics (Harishbhai Tilala et al. 2024).

### 2.4.2 Responsibility and Accountability

Given the inherent significance of responsibility in relation to the integration of AI in healthcare systems, it is imperative that people recognize that all AI systems have limitations, with bias being a significant concern. AI system often operate in an interpretable or non-transparent way, leading to problems with accountability, since it then becomes unclear who would bear responsibility or errors. This lack of accountability for AI use raises worries about the potential safety repercussions of utilizing unverified or unvalidated AI in clinical contexts. As a result, AI systems should be regulated and validated in accordance with the Association for the Advancement of Artificial Intelligence to establish, test, measure, and assess such robots' reliability, performance, safety, and ethical compliance. To guarantee that all parties engaged in the creation, application, and regulation of AI and ML technologies in healthcare are held responsible for their choices and actions, distinct lines of accountability must be established in addition to individual professional duty (Harishbhai Tilala et al. 2024).

Accountability should be therefore distributed among clinicians, to advocate patients' best interests, developers, to validate AI algorithms, healthcare organizations, to establish clear policies and regulatory bodies, to mandate transparency, clinical validation and fairness. To avoid the risk of free riding, a framework with roles and responsibilities should be further implemented, so that all stakeholders involved are accountable for their actions and decisions (Harishbhai Tilala et al. 2024). Healthcare professionals should furthermore be well informed about AI technologies to use them responsibly: they should understand AI systems, and therefore gain knowledge of how AI models function, with also the limitations and bias; there should be an inclusion in the medical training of AI literacy; and finally there should be effective communication so that clinicians have the ability to explain AI-driven recommendations to patients in understandable terms, to provide informed consent (Naik et al. 2022).

# 3. AI Applications in Healthcare Systems

The integration of AI into healthcare systems has ushered in transformative changes, enabling advancements in diagnosis, treatment, and patient management. From early disease detection to improving care delivery, AI technologies are redefining traditional healthcare practices by offering faster, more accurate, and scalable solutions (Stern 2022). AI applications in healthcare are broadly categorized into three key domains: administrative tasks, including activities like scheduling and data management; diagnostic support, such as medical imaging and symptom analysis; and treatment facilitation, encompassing personalized medicine and the generation of tailored treatment recommendations (Stern 2022).

Specifically, for diagnostic support AI has introduced significant advancement through its analytical techniques. For instance, deep learning algorithms leverage neural networks to analyze a wide range of medical images, while natural language processing (NLP) is used to extract diagnostic insights from vast amounts of clinical notes, enabling the integration of multiple data sources to improve diagnostic accuracy (Arefin 2024). Regarding treatment facilitations, AI managed to accelerate drug discovery as much as deliver personalized care. Machine learning techniques indeed facilitate optimized treatment planning and tailored care for individual patients with more precise interventions. Finally, AI applied to administrative processes is automating routine tasks and reducing the burden on clinical staff, for instance machine learning can efficiently match patients to suitable clinical trials based on their eligibility criteria. (Bohr et al. 2020).

*Table 3 Healthcare System's Categories and AI applications' Examples*

| Category | AI model | Examples of applications |
| --- | --- | --- |
| **Administrative Work** | Machine Learning, Automation | Provider Documentation<br>Automated Patient Triaging<br>Data entry |
| **Diagnosis** | Deep Learning, Natural Language Processing | Imaging, Pathology Review<br>Symptom Analysis |
| **Treatment** | Machine Learning | Individual treatment plans<br>Treatment recommendations |

In this chapter, special attention is given to AI applications in detecting and managing dementia, a significant global health concern, and Alzheimer's disease, its most common form. The chapter also delves into diverse AI tools, such as machine learning, deep learning, and natural language processing, which have been harnessed to improve diagnostic accuracy and efficiency. Additionally, innovations like computer-assisted brain scan interpretations, language and movement analysis, and the use of social robots and AI-driven drug discovery highlight the multifaceted contributions of AI to healthcare.

## 3.1 AI Applications in Dementia Diagnosis and Prognosis

Dementia is a global health challenge, currently affecting 50 million older adults, with this number projected to triple to 150 million by 2050 (Li et al. 2022). Dementia is a progressive neurodegenerative condition that impairs memory, thinking, behavior, and daily functioning. It encompasses several subtypes, including Alzheimer's disease (AD), vascular dementia, frontotemporal dementia (FTD), frontotemporal lobar dementia, Huntington's disease, dementia with Lewy bodies, Parkinson's disease, and mild cognitive impairment (MCI) (Tsoi et al. 2023). Current methods for early detection of dementia, however, are often costly, invasive, or impractical for widespread screening. Pre-clinical evaluations largely rely on cognitive tests, which can be time-consuming and lack sensitivity. A dementia diagnosis typically involves a specialist conducting various clinical assessments, including gathering a detailed personal history of cognitive symptoms, performing physical and cognitive exams, and administering blood tests to exclude other conditions that may mimic dementia.

To address the limitations of traditional diagnostic methods, AI presents a promising alternative, it offers a more efficient, automated approach to dementia analysis, potentially reducing both time and costs while improving accessibility for early detection (Li et al. 2022). Current research uses various traditional cognitive tests to detect dementia in its early stages, such as the Mini-Mental State Examination, Addenbrooke's Cognitive Examination-Revised, Montreal Cognitive Assessment, and Clock Drawing Test. While these methods provide useful insights, AI offers enhanced and more accessible digital diagnostic tools, such as computerized cognitive tests, through the aid of machine learning methods (Li et al. 2022). Among these methods there is the support vector machine (SVM), a supervised machine learning algorithm that classifies data by finding an optimal line or hyperplane that maximizes the distance between each class in a N-dimensional space (IBM 2023); the logistic regression, which estimates the probability of an event occurring based on a given dataset of independent variables (IBM 2024) and random forest, a commonly used machine learning algorithm that combines the output of multiple decision trees to reach a single result (IBM 2024).

### 3.1.1 Computer-Assisted Interpretation of Brain Scans

Through brain scans we can gather information about different regions of the brain that are associated with different types of dementia, for example the atrophy in the hippocampus is associated with an early sign of dementia. Regardless these techniques, the interpretations of the scans can be subjective and early stages of dementia might be minimal and very hard to interpret, therefore a computerized method to aid automated interpretation and measurement of brain scans could bring many advantages in diagnosing dementia. Two main methods have been used: deep learning and machine learning.

Machine learning methods have been developed to detect the disease via neuroimaging data availability. Different methods (such as Gaussian process and support vector machine) have been applied to two large longitudinal data sets that together comprise interval MRI and PET scans from almost 2,000 participants with dementia, MCI or healthy controls (Li et al. 2022).

Lately also Deep Learning has been used greatly for data processing: it imitates the working of the human brain and can merge complicated feature extraction and classification in solving complex problems. Deep learning methods have been giving reassuring results by showing promising accurate results, however, a huge amount data is still required for these models.

Also, the hidden Markov Model, a reinforcement learning method, is particularly suitable for detecting the progression of dementia by analyzing sequence neuroimaging data (Li et al. 2022).

### 3.1.2 Speech and Language Tests

Language impairment is an early sign of cognitive disorders, with symptoms including aphasia, frequent pauses, and reduced vocabulary. AI leverages Natural Language Processing (NLP) to analyze speech and language patterns in dementia patients. Deep learning models, particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), are used to process large volumes of speech data to detect dementia-related language changes. Common AI-based speech tests involve extracting relevant features from language samples and using machine learning or deep learning classifiers to identify dementia-consistent patterns (Tsoi et al. 2023).

### 3.1.3 Movement Tests

Movement tests, including gait analysis and hand and eye movement monitoring, offer another pathway for identifying digital biomarkers of dementia. We refer to digital biomakers as objective, quantifiable physiological and behavioral data that are collected and measured by means of digital devices (Harms et al. 2022), and specifically a digital biomarker of dementia is a measurable, objective indicator derived from digital technology that helps detect or predict the onset, progression, or severity of dementia-related cognitive decline (Gold et al. 2018). For instance, changes in walking patterns or fine motor skills may signal early cognitive decline. AI can enhance the accuracy and scalability of these movement assessments, making it possible to identify dementia markers in non-invasive ways.

### 3.1.4 Dementia Care and Treatment

AI was also used for dementia care and treatment: the aging population requires indeed more care and to overcome the lack of caregivers, researchers have been testing the use of social robots. These robots can provide support in daily activities for those who have MCI or are in the early stage of dementia. AI is also instrumental in accelerating drug discovery for dementia by analyzing vast datasets to identify potential new treatments. This data-driven approach can significantly reduce the time and costs associated with traditional drug development, providing hope for more effective dementia therapies (Tsoi et al. 2023).

## 3.2 AI Applications in Alzheimer's Disease

Alzheimer's disease (AD) is an irreversible and incurable neurodegenerative disorder associated with a progressive deficiency in memory and cognitive abilities, loss of thinking abilities, and problems in daily activities (Fathi et al. 2022). AD is now affecting over 35 million people worldwide and this number double in the next two decades. To understand its effects on brain structure and function, there are multiple brain techniques that have been used, such as structural magnetic resonance imaging (sMRI), functional magnetic resonance imaging (fMRI), diffusion tensor imaging (DTI), and positron emission tomography (PET) (Li et al. 2021). Visual assessment is no longer enough to study this illness, and AI provides the necessary tools to dive deeper into understanding this complex condition.

Different types of deep models are used, and they can be divided in supervised (Convolutional Neural Network (CNN), Deep Neural Network (DNN), Deep Polynomial Network (DPN), and Recurrent Neural Network (RNN), and unsupervised, which consist of Auto-encoder (AE) and Deep Boltzmann Machine (DBM) algorithms. (Fathi et al. 2022)

### 3.2.1 Supervised Learning Approaches

Starting from supervised learning, a popular method is the Convolutional neural network (CNN): it has a multilayer hierarchical architecture and is one of the best techniques for analyzing imaging tasks. The most popular architectures are the following: ResNet (Residual Network), VGG (Visual Geometry Group), a simpler design with fixed convolutional layers, and DendeNet, which connects each layer to every other layer to enhance feature reuse and improve learning efficiency (Fathi et al. 2022).

Furthermore, Deep Neural Network (DNN) is a type of deep model that has the same architecture as traditional artificial neural networks, but it has more hidden layers, which aim to create complex networks and extract more high-level features from the data. DNNs are applied in AD for tasks like predicting cognitive decline, classifying disease stages and processing non-imaging data such as genomic profiles or clinical metrics (Fathi et al. 2022).

Deep polynomial network (DPN) is a method that applies polynomial (linear or quadratic) function on inputs of each neuron. This model is used in AD primarily for multimodal data analysis, for example combining MRI and PET data in a two-stage process: firstly, extracting features from each modality using DPN module, and then integrating these features to improve diagnostic accuracy (Fathi et al. 2022).

Recurrent Neural Network (RNN) is an artificial neural network with a directed-graph shape structure, are designed to process sequential data. These modules are effective in AD to analyze time-series data.

### 3.2.2 Unsupervised Learning Approaches

Unsupervised models focus on identifying hidden patterns in unlabeled data, which is beneficial in AD research when labeled datasets are scarse or costly to obtain (Fathi et al. 2022).

Auto-encoders (AE) are neural networks designed to learn compressed representations of data, making them useful for extracting features from complex AD datasets without labeled outcomes. AEs can identify anomalies or changes in brain images that may suggest the onset of Alzheimer’s (Fathi et al. 2022).

Restricted Boltzmann Machine (RBM) and Deep Belief Network (DBN) are generative models that learn from data distributions to extract high-level patterns. RBM are also the buildingblocks for deeper architectures like DBNs. They are used in AD research to recognize brain image patterns that indicate disease progression (Fathi et al. 2022).

Deep Boltzmann Machine (DBM) are an extension of RBMs, structured to learn even more intricate data representations. In AD diagnosis, DBMs analyze multi-modal datasets, such as combining imaging with genetic data, to uncover complex relationships associated with the disease (Fathi et al. 2022).

## 3.3 Challenges of Deep Learning

There are some challenges that can arise from deep learning models, such as data scarcity, since supervised models require large, labeled datasets which are often unavailable, therefore unlabeled data can be a possible solution. Interpretability can be considered as a limitation since deep learning approaches are sometimes lacking transparency (Fathi et al. 2022; Jo et al. 2019). The application of Artificial Intelligence in diagnosing dementia and Alzheimer's disease highlights the versatility and scope of AI technologies in addressing these neurodegenerative conditions. While both areas leverage advanced tools like machine learning and deep learning, their approaches and focuses vary due to the distinct nature of the diseases and their diagnostic challenges. *Table 4* provides a comparative overview of the primary AI technologies, data requirements, diagnostic techniques, and associated challenges for dementia and Alzheimer's disease. By summarizing these aspects, it underscores how tailored AI methodologies are shaping early detection, prognosis, and care for these conditions.

*Table 4 AI Applications in Dementia Diagnosis and Alzheimer's Disease Diagnosis*

| Activity | Dementia Diagnosis | Alzheimer's Disease Diagnosis |
|---|---|---|
| **Primary AI Technology** | • Machine Learning (Support Vector Machine, Logistic Regression, Random Forest)<br>• Deep Learning (CNN, RNN, and other neural networks)<br>• Hidden Markov Models | • Deep Learning (CNN, DNN, DPN, RNN)<br>• Unsupervised Learning (Auto-encoders, DBM, RBM, DBN) |
| **Imaging Methods** | • Neuroimaging (MRI and PET scans analyzed using ML models like Gaussian Process and SVM)<br>• Deep learning models for automated feature extraction | • Convolutional Neural Networks (CNN) for MRI and PET analysis<br>• DPN for multimodal feature integration (MRI and PET) |
| **Data Requirements** | Large datasets for training deep learning models; limited by fragmented or incomplete data for early-stage dementia | Substantial neuroimaging and clinical data for training supervised and unsupervised models |
| **Cognitive Test Integration** | • Computerized Cognitive Tests using ML algorithms<br>• Examples: Mini-Mental State Exam, Montreal Cognitive Assessment enhanced by AI | Often integrated with imaging-based methods but less emphasized in specific Alzheimer's studies |

| | | |
|---|---|---|
| **Speech and Language Analysis** | • Natural Language Processing (NLP) used to assess language dysfunction, such as aphasia, reduced vocabulary, and pauses<br>• Methods: CNN, RNN | Not explicitly focused on speech and language in current Alzheimer's applications |
| **Movement Tests** | Screening of gait, hand, and eye movements using AI models | Rarely mentioned in Alzheimer's-specific diagnostics |
| **Deep Learning Architectures** | • CNNs, RNNs for language and movement analysis<br>• Models focus on early detection of subtle symptoms | • Advanced CNN models such as ResNet, VGG, and DenseNet<br>• DNN and DPN for high-level feature extraction |
| **Specialised Techniques** | Hidden Markov Models for tracking disease progression through neuroimaging | DPN for two-stage feature extraction and multimodal data integration |
| **AI in care and Treatment** | • Social robots for dementia care<br>• AI-assisted drug discovery | Focus on predicting disease progression and supporting drug trials |
| **Accuracy and Challenges** | Promising accuracy with Deep Learning methods but limited by the availability of large-scale data | • CNNs and DNNs show strong results in imaging-based tasks but also require vast datasets<br>• Unsupervised methods are still being refined for optimal accuracy |

# 4. Comparative Analysis of AI in Dementia, Alzheimer's Disease and Other Diseases

AI has revolutionized the healthcare landscape by offering innovative solutions for diagnosis, treatment, and patient care across a variety of diseases. In the context of dementia and Alzheimer's disease, the integration of AI technologies has enabled early detection, disease progression monitoring, and the development of tailored treatment strategies, addressing the urgent needs posed by these neurodegenerative disorders. However, the transformative impact of AI is not limited to these conditions, AI methods such as machine learning, deep learning, and natural language processing are being leveraged to identify subtle biomarkers, enhance diagnostic accuracy, and personalize medical interventions. Each condition presents unique challenges, requiring AI to adapt its methodologies to suit specific data types, disease mechanisms, and patient needs. The following table (*Table 5*) provides a comparative overview of AI applications in dementia and Alzheimer's diagnosis versus other diseases, illustrating the shared technologies, specialized techniques, and innovations that define AI's role in modern medicine. This analysis highlights both the versatility of AI in addressing diverse healthcare challenges and its capacity to deliver targeted solutions for specific conditions, driving progress in early diagnosis, precision medicine, and patient outcomes.

*Table 5 Comparative Analysis of Dementia, Alzheimer's Disease, Loss Memory Diseases and Non-Memory Loss Diseases*

| Criteria | Dementia | Alzheimer's Disease | Other Memory Loss Disease | Non-Memory Loss Disease |
|---|---|---|---|---|
| **AI Technology** | Deep Learning, NLP, Machine Learning | Deep Learning and Recurrent Neural Networks | Basic ML and statistical methods | Machine Learning, Imaging AI, NLP |
| **Diagnostic Tools** | Brain imaging, Speech/Language Analysis | Brain scans, Genomic data, Biomakers | Cognitive Tests (traditional or digital) | Imaging, Blood Makers, Symptoms analysis |
| **Data Requirement** | High-volume specch and imagin datasets | Multi-modal (MRI, PET, genomic data) | Limited and disease-specific datasets | Generalised large datasets, EHRs |
| **Costs** | Cost-effective for early screening, reduces manual diagnostic work, requires investment in robust AI training datasets | Expensive due genomic data handling and advanced imaging | Limited cost reduction due to fewer AI applications, moderate implementation costs | Cost saving in diagnostic and treatment planning |
| **Unique AI Contributions** | Identifying subtle neurodegenerative patterns | Predictive cognitive decline | Efficient screening tools | Early and non-invasive detection methods |
| **Ethical Considerations** | Data security, Algorithmic bias | Data sharing of genomic and clinical data raises significant privacy and concerns concerns | Equal access to AI tools, risk of misdiagnosis due to smaller datasets | Challenge with global scalability and fairness, |

# 5. Conclusion and Future Research

## 5.1 Opportunities for Future Research

There are numerous topics that still need to be investigated regarding the use of AI in healthcare systems. For example, greater research is needed into ways that train AI systems in collaboration with human experts and carers, such as interactive simulation training and community-based modelling approaches (Arefin 2024). Furthermore, new technologies must be deployed to further the specialised application of AI to even more particular individual medical and surgical specialities, such as customising AI assistants to specific guidelines, diagnostic and treatment criteria. Machine learning techniques will be able to produce treatment options based on the patients' medical history (Javaid et al. 2022). Most importantly, privacy regulations and data sharing must be enacted to coordinate worldwide stakeholders and overcome the fragmentation of health data standards (Arefin 2024). To prevent the time-consuming and expensive process of manually annotating samples into their respective categories, it is critical to build ways to annotate unlabelled data samples, such as active learning approaches (Kumar et al. 2023).

## 5.2 Final Reflections

This thesis investigated the application of artificial intelligence technologies in addressing diverse healthcare challenges across dementia, Alzheimer’s disease and its capabilities to revolutionize diagnostic accuracy, cost-effectiveness and treatment personalization through models such as machine learning, deep learning and natural language processing. From a broader perspective, this thesis addresses the unique contributions of AI in transforming healthcare systems. However, ethical considerations must remain central to the development and deployment of these technologies.

In conclusion, AI holds immense promise for improving healthcare outcomes across a wide spectrum of diseases. By addressing the outlined challenges and fostering ethical innovation, AI can lead to more inclusive and effective healthcare systems, ensuring that the benefits of this technology are realized globally.

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