# Why Words Matter: Medical Terminology in Artificial Intelligence-Enabled Healthcare

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## Abstract

This paper emphasizes the role of medical terminology in the effective and responsible use of artificial intelligence (AI) in healthcare. It examines how precise clinical language shapes data labeling, algorithmic interpretation, and clinical decision support systems. Drawing on recent peer-reviewed medical and biomedical informatics literature, the paper identifies key termini technici related to cognitive decline, women's health, and health data infrastructure. The analysis highlights how inconsistent documentation, ambiguous clinical transitions, and patient-reported symptoms can affect data quality, bias, and reliability in AI-enabled healthcare systems.

**Keywords:** artificial intelligence in healthcare, medical terminology, dementia, Alzheimer's disease, mild cognitive impairment, subjective cognitive decline, clinical decision support, precision medicine, menopause, perimenopause, electronic health records, vasomotor symptoms

## I. Introduction

Artificial intelligence (AI) is becoming widely adopted in healthcare systems to support diagnosis, monitoring, and individualized patient care, as well as in healthcare business management. <u>Accurate and standardized medical terminology is foundational to the safe, effective, and equitable application of artificial intelligence in healthcare, as it directly shapes data quality, algorithmic interpretation, and clinical decision-making.</u>

Medical terminology does more than describe a disease; in AI, it defines how clinical states are labeled within datasets, algorithms, and decision-support tools. As these technologies advance, accurate medical terminology remains essential for ensuring clear and accurate communication, valid output interpretation, transparency, and patient safety. The following identifies and analyzes example key termini technici drawn from recent peer-reviewed medical journal articles. The purpose of this analysis is to demonstrate how accurate medical language underpins effective and responsible AI implementation.

## II. Background

Medical terminology has long served as the standardized language that enables consistency across the healthcare system. Historically, clinical terminology developed through physician-led classification systems and paper-based documentation. This evolved into formalized vocabularies such as the International Classification of Diseases (ICD) and standardized clinical lexicons. These systems were originally designed to support human interpretation and administrative processes rather than computational analysis.

With the widespread adoption of electronic health records (EHRs), medical terminology became embedded within digital infrastructures, transforming clinical language into structured data elements that could be stored, shared, and analyzed at scale. In the context of AI, terminology directly influences how diseases, symptoms, and medical transitions are catalogued and acted upon within electronic health records and machine learning models. Consequently, terminology that was once primarily descriptive now plays a critical role in determining data quality, model training, and model output.

This change has revealed significant challenges, as conditions such as dementia, perimenopause, and menopause are frequently underdocumented, inconsistently coded, or described using imprecise language. This complicates algorithmic identification and longitudinal monitoring. These gaps are particularly problematic as healthcare more and more relies upon real-world data to support AI models. Understanding and correctly applying medical terminology is essential to reducing misclassification, mitigating bias, and ensuring that AI systems produce safe, reliable, and clinically meaningful outputs.

**III. Body: Identification and Analysis of Medical Terminology**

The following termini technici examined in this paper were selected from recent peer-reviewed medical journal articles. Primary sources included publications from

*Alzheimer's & Dementia, JAMIA Open, Journal of Biomedical Informatics*, and were supplemented with guidance from the National Institute on Aging, the North American Menopause Society, Mayo Clinic, and HealthIT.gov. Terms were chosen based on their appearance in AI-enabled healthcare research, their importance to clinical decision-making, and their known challenges related to documentation, coding, or patient-reported variability. Together, these sources reflect how medical terminology directly shapes data quality and interpretability in AI-driven healthcare systems.

**Term:** Dementia

**Definition:** Dementia is a clinical syndrome characterized by a progressive decline in cognitive function that is severe enough to interfere with independent daily activities (National Institute on Aging, 2024).

**Context: "**Caregivers requested a cognitive assessment for dementia to provide a personalized care plan."

**Importance:** Dementia is linked to morbidity, caregiver burden, and healthcare utilization, making an accurate diagnosis essential for timely intervention and mitigation as well as care planning.

**Term:** Alzheimer's Disease

**Definition:** Alzheimer's disease is a neurodegenerative disorder and the most common cause of dementia, marked by progressive memory and cognitive decline (National Institute on Aging, 2024).

**Context: "**The patient's advanced Alzheimer's disease required increased cognitive monitoring intervals."

**Importance:** The early and accurate identification of the disease supports risk assessment, long-term planning, and the potential for use of trial therapeutic approaches.

**Term:** Mild Cognitive Impairment

**Definition:** Mild cognitive impairment is a condition that involves measurable cognitive decline but does not yet significantly hinder daily functioning (Mayo Clinic, 2024).

**Context:** "According to the study by Zhao et al., mild cognitive impairment is an intermediate clinical state between normal aging and dementia. (Zhao et al., 2026)"

**Importance:** Each year, between 10-15% of patients with mild cognitive impairment are diagnosed with dementia (Alzheimer's Association, 2026). Early identification of targeted intervention may mitigate irreversible functional decline.

**Term:** Subjective Cognitive Decline

**Definition:** Subjective cognitive decline refers to a self-experienced, persistent decline in cognitive capacity, usually memory, compared with a previously normal state, despite normal performance on standardized objective cognitive tests (Jessen et al., 2024)

**Context:** "Subjective cognitive decline is an early indicator of future potential cognitive impairment."

**Importance:** Subjective cognitive decline illustrates the value of patient-reported symptoms and helps identify individuals at an elevated risk for more significant problems.

**Term:** Clinical decision support

**Definition:** Clinical decision support is the health information technology system designed to provide clinicians with individualized assessments or recommendations to aid clinical decision making.

**Context:** “In AI-enabled dementia care research, clinical decision support systems are discussed as ways to integrate patient data and care guidelines to assist clinicians.”

**Importance:** Clinical decision support systems have the potential to enhance patient safety and care quality, particularly in complex conditions such as cognitive decline and dementia.

**Term:** Precision Medicine

**Definition:** Precision medicine is an approach to healthcare that tailors prevention, diagnosis, and treatment to individual variability in genetics, environment, and lifestyle (Mukherjee at al., 2022).

**Context:** “Precision medicine focuses a care plan on a specific individual rather than on the population at large.”

**Importance:** The JAMIA Open article, *Digital twins to enable better precision and personalized dementia care,* frames digital twins as an enabling technology for precision medicine in dementia care by creating patient-specific computational representations that integrate diverse data sources, including clinical assessments, biomarkers, imaging, behavioral data, and longitudinal health records. This allows researchers to simulate disease trajectories and evaluate care plans at the level of the patient rather than the population.

**Term:** Menopause

**Definition:** Menopause is the permanent cessation of menstruation following twelve consecutive months of amenorrhea due to ovarian follicular depletion and without pathological causes (North American Menopause Society, 2024).

**Context:** “Many female patients report being ‘in menopause’ due to a cluster of symptoms which can range from hot flashes to ringing in ears to brittle bones to lack of muscle tone to a general malaise.”

**Importance:** Menopause significantly affects nearly every body system of a woman, including cardiovascular, metabolic, and cognitive health, and can be a determining factor in the quality of life.

**Term:** Perimenopause

**Definition:** Perimenopause is the transitional phase that precedes menopause, that is characterized by hormonal fluctuations and variable symptoms (North American Menopause Society, 2024).

**Context**: “Perimenopause is hard to pinpoint or detect algorithmically due to inconsistent clinical documentation and patient reports. (Zhang et al., 2021).

**Importance:** Perimenopause is a good example of how biological transitions introduce data complexity, incomplete data, and labeling ambiguity, all of which directly affect the reliability of AI models trained on real-world healthcare data.

**Term:** Electronic Health Records (EHRs)

**Definition:** Electronic health records are digital records containing patients' medical histories, diagnoses, medications, treatment plans, and clinical notes (HealthIT.gov, 2024).

**Context:** **“**EHRs serve as the primary data source for a complete medical picture of a patient.”

**Importance:** The inconsistency of EHR data will influence AI reliability, bias, fairness, and provider trust.

**Term:** Vasomotor Symptoms

**Definition:** Vasomotor symptoms refer to episodes of hot flashes and night sweats caused by the dysregulation of thermoregulatory controls, common during perimenopause and menopause because of a fluctuating estrogen level (North American Menopause Society, 2024).

**Context:** “The patient reports frustration with vasomotor symptoms, including night sweats.”

**Importance:** Vasomotor symptoms are significant because they represent high-frequency, patient-reported, temporally dynamic symptoms, the type of data that benefits from longitudinal modeling and personalized analysis.

## IV. Conclusion

In conclusion, this paper addressed the critical role of medical terminology in the responsible and effective application of AI within healthcare systems. As AI increasingly supports diagnosis, monitoring, and clinical decision-making, the precision with which medical conditions, symptoms, and biological transitions are defined and documented becomes foundational to patient safety, algorithmic accuracy, and clinical trust.

Through the deeper study of key termini technici in this paper, it was reinforced how medical language directly shapes data quality, model performance, and interpretability in AI-enabled healthcare. These terms illustrated how inconsistent documentation, ambiguous clinical transitions, and underrecognized patient-reported symptoms can introduce bias, misclassification, and inequity into AI systems when not rigorously defined and applied.

The key takeaway is that successful AI implementation in healthcare depends as much on technical innovation as it does on linguistic and clinical precision. Accurate, standardized medical terms enable meaningful data integration, support individualized care through precision medicines, ad reinforces clinician oversight within AI-driven decision support systems. As healthcare continues to adopt AI at scale, mastery of governance of medical terminology will remain essential to ensuring that technological advancement translates into safe, equitable, and patient-centered care.

## Conflict of Interest Declaration

The author declares no conflict of interest related to this assignment.

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