

Understanding AI's Impact on Clinical Decision-Making: A Comparative Study of Simple and
Complex Primary Care Scenarios

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Clinical decision-making is a complex cognitive process shaped by multiple factors, including cognitive biases, clinical context, and the integration of healthcare technologies. This thesis investigates how the introduction of artificial intelligence (AI)-enabled decision support tools influences clinical reasoning processes in primary care settings. Using Cognitive Work Analysis (CWA), Decision Ladder (DL) frameworks, and content analysis methods, this study qualitatively examines clinician decision-making behaviors across traditional electronic medical record (EMR) environments and AI-supported scenarios. Fourteen clinicians from Ontario, Canada, participated in scenario-driven sessions involving routine (uncomplicated urinary tract infections) and complex (mental health distress) cases. Analysis revealed distinct cognitive shortcuts, shifts, and reliance patterns influenced by AI. Specifically, AI systems reinforced heuristic-driven decisions for routine cases but introduced additional cognitive demands in complex scenarios due to information integration requirements. Visual emphasis in the DLs highlighted AI-driven cognitive shortcuts and behavior modifications. Limitations include scenario-driven constraints and a small, region-specific sample with similar EMR and AI experiences. Future research should explore mid-complexity scenarios, incorporate diverse clinician populations, and evaluate long-term effects of AI integration on clinical reasoning. This work contributes to understanding the nuanced interplay between cognitive processes and AI technology, informing user-centered design strategies for healthcare decision support systems.

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Dedication

To Mom, Dad, and my sister. I wouldn't be here without you.

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List of Abbreviations

AI	Artificial Intelligence
AUC	Area Under the Curve
BUC	Bayesian Uncertainty Calculator
CASP	Critical Appraisal Skills Programme
CBT	Cognitive Behavioral Therapy
CDM	Cognitive Decision-Making
CDS	Clinical Decision Support
CDSS	Clinical Decision Support System
CHR	Collaborative Health Record
CIS	Clinical Information System
CPP	Cumulative Patient Profile
CSE	Clinical Setting Environment
DL	Decision Ladder
EHR	Electronic Health Record
EMR	Electronic Medical Record
EPR	Electronic Patient Record
FHO	Family Health Organization
FHN	Family Health Network
FHT	Family Health Team
GAD	Generalized Anxiety Disorder
GAD-7	Generalized Anxiety Disorder 7-item Scale
HCI	Human-Computer Interaction
ICU	Intensive Care Unit
MDD	Major Depressive Disorder
ML	Machine Learning
MSE	Mental Status Examination
NASA-TLX	NASA Task Load Index
NLP	Natural Language Processing
OCR	Optical Character Recognition
PCP	Primary Care Physician
PGHD	Patient-Generated Health Data
PHQ	Patient Health Questionnaire
PHQ-9	Patient Health Questionnaire-9

qSOFA	Quick Sequential Organ Failure Assessment
RA	Research Assistant
REB	Research Ethics Board
SEIPS	Systems Engineering Initiative for Patient Safety
SIRS	Systemic Inflammatory Response Syndrome
SDM	Shared Decision Making
SOAP	Subjective, Objective, Assessment, Plan
TrAAIT	Trust and Acceptance of Artificial Intelligence Tools
UCD	User-Centered Design
UI	User Interface
UI/UX	User Interface / User Experience
UIMA	Unstructured Information Management Architecture
UTI	Urinary Tract Infection
UTAUT	Unified Theory of Acceptance and Use of Technology
UX	User Experience
xAI	Explainable Artificial Intelligence
xAI-EWS	Explainable Artificial Intelligence Early Warning Score

Chapter 1

Introduction

1.1 Background

Every day, thousands of Canadians receive primary health care (PHC) services, usually from a nurse practitioner, general practitioner, or family physician (CIHI, 2024). Primary care is the element within primary health care that focusses on health care services, including health promotion, illness and injury prevention, and the diagnosis and treatment of illness and injury (Government of Canada, 2012)

Primary care serves as the cornerstone of healthcare systems worldwide, and in Canada, it represents patients' first and most frequent point of contact within the healthcare system. Primary care physicians (PCPs) in Canada are responsible for comprehensive patient care, managing a wide range of health issues, and facilitating coordination across specialized care services (Hutchison et al., 2011) Given the diversity and complexity of patient presentations in primary care, efficient information management and decision-making processes are essential to high-quality patient care outcomes.

Over the past few decades, Electronic Medical Records (EMRs) have emerged as indispensable tools in primary care practices, providing structured digital storage for patient data, facilitating information retrieval, enhancing communication among care providers, and supporting clinical decision-making (Boonstra & Broekhuis, 2010; Ludwick & Doucette, 2009).. EMRs have significantly reduced reliance on paper-based records, thereby minimizing administrative burdens, improving documentation accuracy, and ultimately enhancing care quality and patient safety (Canada Health Infoway, 2022). According to Canada Health Infoway (2022), approximately 93% of PCPs across Canada now utilize EMRs. Over time, EMRs have become widely used in primary care, enhancing clinicians' ability to deliver care.

More recently, AI technologies have begun to be integrated into EMRs, presenting opportunities to further transform primary care practices. AI systems within EMRs can automate administrative tasks, assist in clinical diagnostics, generate tailored recommendations for patient care, and support clinicians in synthesizing patient information more effectively (Davenport & Kalakota, 2019; DuBois, 2019). To exploit AI's capabilities in this area, it is essential to investigate how AI can be carefully crafted and incorporated into primary care environments, making sure it enhances clinical practices and, in the end, aids in providing high-quality primary care.

1.2 Problem Statement

By international standards, Canada has a low physician-to-population ratio (Hutchison et al., 2011). Therefore, with a shortage of clinicians and a growing patient population, the healthcare industry is often overworked, placing clinicians under a high workload. In a hospital setting, clinicians are typically required to make dynamic or real-time decisions that are interdependent and constrained by the clinical situation. According to Cognitive Load Theory (CLT), an excessive workload can negatively impact decision-making. In other words, clinicians who are overwhelmed with complex tasks and time constraints often experience a decline in their clinical decision-making efficiency. Evidence also shows that reducing clinical workload can positively influence decision-making quality in clinicians and improve patient outcomes (Shamszare & Choudhury, 2023).

Despite the substantial integration of EMRs into primary care practices and the increasing adoption of AI technologies, a significant knowledge gap remains regarding the impact of AI-assisted EMRs on clinicians' cognitive workflows and decision-making processes. Clinical decision-making is inherently complex, involving multiple cognitive tasks such as information gathering, interpretation, synthesis, and judgment (S. Lin, 2022). Integrating AI into EMRs introduces new dynamics into these cognitive processes, potentially altering how clinicians process and synthesize information during patient consultations. Existing literature indicates variations in clinician acceptance and reliance on AI, contingent upon the

complexity of clinical scenarios (Jones et al., 2023; Shamszare & Choudhury, 2023; Sivaraman et al., 2023). Lastly, studies have identified several factors hindering the adoption of AI, including the lack of clinician involvement in AI development, low trust in the technology, limited explicability of AI algorithms, and unclear policy around AI accountability (Shamszare & Choudhury, 2023).

Therefore, understanding how cognitive work and decision-making processes differ when using AI-assisted EMRs compared to traditional EMRs, particularly across varying levels of clinical complexity, is fundamental (Scott et al., 2024). Addressing this gap can help optimize the integration and use of AI in primary care, ensuring that AI systems align effectively with clinical practice needs and enhance, rather than hinder, clinician performance and patient outcomes.

1.3 Research Questions

The primary aim of this thesis is to explore and understand the cognitive and decision-making implications of integrating AI-assisted tools into EMRs within primary care settings. Specifically, this study addresses the following research questions:

1. In what ways does cognitive work vary when using AI-assisted tools in simple versus complex clinical scenarios?
2. How do clinicians' decision-making processes change when using AI-assisted EMR modules compared to traditional EMR systems, and do these changes differ between routine (simple) and complex scenarios?
3. What are the key differences in information processing and synthesis between traditional and AI-assisted EMR use during patient consultations, and how do these differences manifest in simple versus complex cases?

I was able to take advantage of another ongoing study by Krizia Francisco to study these research questions. Francisco's study was a qualitative study design to understand the cognitive impact of AI-integrated EMRs comprehensively (K. Francisco, 2025). She

conducted semi-structured interviews with primary care clinicians, offering in-depth qualitative insights. Interviews were conducted using standardized clinical scenarios representing simple and complex patient consultations, supplemented by situational follow-up questions to elucidate clinicians' cognitive processes clearly. I helped with her data analysis as one of the theme coders for her work (K. Francisco, 2025).

While Francisco's focus was on exploring the overall cognitive implications of AI integration, my work extends and differentiates from hers in three key ways. First, I introduce a comparative lens by explicitly analyzing differences between simple vs. complex cases (Question 1) and AI vs. non-AI scenarios (Question 2), which were not central to her analysis. Second, I incorporate a cognitive systems engineering approach through the use of decision ladders, enabling a structured mapping of clinician reasoning processes, an analytic method not used in her thesis. Third, I synthesize the decision ladder and content analysis findings to generate actionable design and research recommendations for AI integration in clinical workflows.

From this foundation I realized that she had not explored the differences in decision making between the simplex and complex scenarios (Question 1) and the AI and non-AI scenarios (Question 2). My data analysis utilized decision ladder and content analysis methods, aiming to map cognitive workflows systematically and identify patterns and themes related to AI's integration and its implications on clinician decision-making (Question 3).

1.4 Significance of Study

This research aims to contribute to the understanding of how AI integration into EMRs affects clinicians' cognitive processes and decision-making practices within primary care. By clarifying cognitive workflow variations between traditional and AI-assisted systems across diverse clinical complexities, this study provides critical insights for healthcare technology developers, policymakers, and practitioners. Specifically, findings from this research will inform the design and implementation of more intuitive and effective AI-driven EMR systems tailored to clinicians' needs, ultimately aiming to enhance clinical decision-making

quality, efficiency, and patient outcomes. Additionally, highlighting potential challenges related to clinician acceptance, trust, and concerns about autonomy and bias can guide future training initiatives, regulatory frameworks, and professional guidelines surrounding AI usage in healthcare.

1.5 Thesis Structure

The thesis is structured as follows:

IntroductionChapter 1 presents the research topic, outlines the research objectives, and explains the study's overall contribution. This chapter also introduces the structure of the thesis.

Chapter 2 serves as a literature review of existing research, theories, and frameworks relevant to the integration of AI into EMRs in primary care settings. It provides a comprehensive overview of ambient scribe technology, including ethical considerations and the current technological landscape. The chapter also explores the role of human factors in the adoption and effectiveness of AI scribes.

Chapter 3 outlines the study's mixed-method design, including the methodological framework, participant eligibility criteria, recruitment strategies, and details of data collection and analysis procedures. This study design is the work of Krizia Francisco but is included here to provide the context for understanding the results.

Chapter 4 presents the study's findings. This includes a description of the study population (also referenced in Chapter 5), as well as the quantitative results and qualitative insights that address research objectives 1 and 2.

Chapter 5 offers an in-depth discussion of the findings in relation to prior literature and theoretical frameworks. It interprets the results, examines design implications for user-

centered AI integration in clinical workflows, and provides recommendations for practice. The chapter also addresses study limitations, suggests directions for future research, and concludes with reflections on the broader implications of AI adoption in primary care.

Chapter 2

Literature Review

The literature review chapter aims to provide an extensive exploration of existing research, theories, and frameworks relevant to the integration of AI into EMRs in primary care settings. This review will contextualize the current state of knowledge and identify areas for further research by examining several interconnected themes outlined below.

2.1 Artificial Intelligence in Primary Care

AI represents a transformative potential within primary care, driven by rapid advancements in technology, data availability, and increasing demands for efficient and high-quality patient care. Despite considerable enthusiasm and ongoing research efforts, the integration of AI into primary care is still in its infancy, requiring substantial exploration of its optimal roles and limitation (Kueper et al., 2020; S. Lin, 2022).

2.2 Clinical decision support systems (CDSSs)

Clinical decision support systems (CDSSs) are increasingly integrated into healthcare settings to improve patient outcomes, reduce medical errors, and enhance clinical efficiency by providing clinicians with evidence-based recommendations at the point of care (Z. Chen et al., 2023); Figure 2-1 depicts the history of CDSS and its evolution. In recent years, AI-powered Clinical Decision Support Systems (AI-CDSSs) have emerged as one of the most common applications of AI in primary care. These systems help automate documentation, assist with clinical reasoning, and offer tailored recommendations based on patients' electronic records (Gomez-Cabello et al., 2024; Kueper et al., 2020).

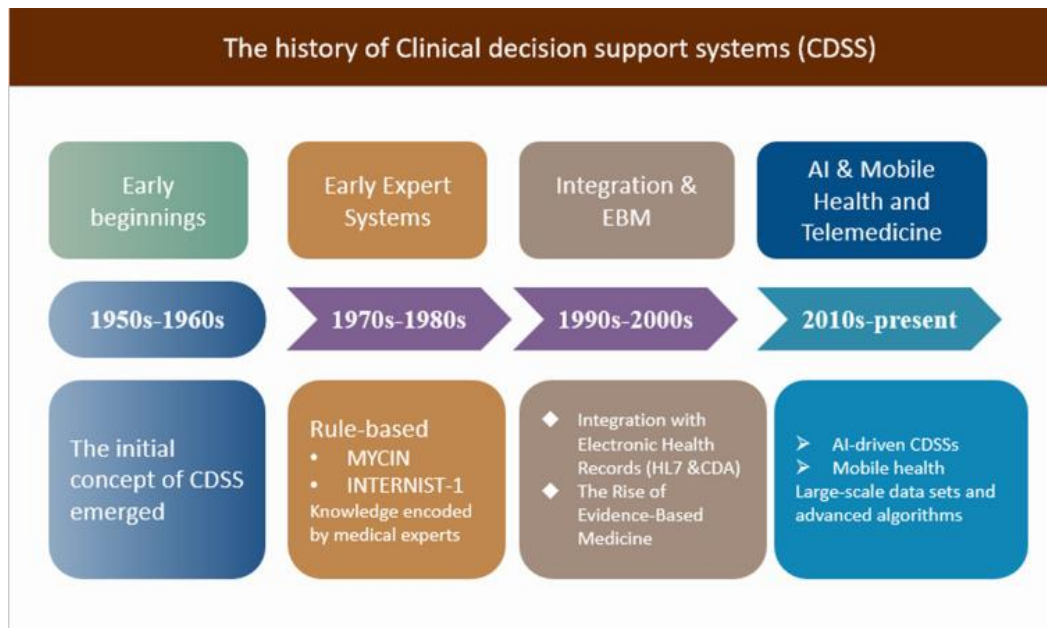


Figure 2-1 The History of Clinical Decision Support Systems Adapted from (Z. Chen et al., 2023)

Studies show AI-CDSSs can support diagnosis, reduce prescription errors, and improve adherence to clinical pathways. However, issues such as alert fatigue, poor integration with existing EHR systems, and irrelevant recommendations continue to hinder clinician satisfaction and workflow efficiency (Gomez-Cabello et al., 2024).

Physician skepticism and mistrust in AI-CDSSs have also been attributed to concerns over data privacy, explainability of outputs, low contextual adaptability, and fears of being replaced (Gomez-Cabello et al., 2024). Additionally, barriers like increased time burdens, limited local customization, and lack of alignment with real-world clinical settings have been observed, particularly when confidence scores or recommendations do not align with clinician expectations.

2.2.1 AI in Electronic Medical Records (EMRs)

The integration of AI into EMRs represents a pivotal evolution in digital health infrastructure. By leveraging the growing availability of clinical data, AI-enhanced EMRs

hold the potential to significantly improve information retrieval, diagnostic accuracy, risk stratification, and overall clinical efficiency (Mintz & Brodie, 2019; Ye et al., 2024a). AI can analyze large volumes of structured and unstructured data such as vital signs, laboratory results, clinical notes, and imaging data, aiding clinicians by automating information retrieval and summarization (Mehta & Devarakonda, 2018). Research has shown the integration of AI into EMRs enhances real-time patient data interpretation and risk stratification. Systems utilizing AI to process patient-generated health data (PGHD) or radiological records provide tailored insights that support timely and accurate diagnoses (Mintz & Brodie, 2019; Ye et al., 2024).

AI applications in EMRs are wide-ranging. Natural language processing (NLP) techniques can now extract clinically relevant terms, such as diseases, symptoms, medications, and modifiers, from free-text notes with increasing ease. This capability has been strengthened by innovations such as IBM's Unstructured Information Management Architecture (UIMA) and the Clinical Text Analysis and Knowledge Extraction System (cTAKES) developed at Mayo Clinic (Mehta & Devarakonda, 2018; Yang et al., 2022). These tools enable deeper insight from clinical visit notes, lab reports, and imaging data, enhancing the utility of EMRs beyond numerical inputs.

As digital imaging and EHRs proliferate, radiology and pathology reports have become rich sources of data for AI models. Machine learning (ML) is now being employed to analyze this information, aiding in diagnosis and treatment planning. For instance, ambient AI systems can transcribe and structure patient-provider conversations in real time, functioning like a digital scribe to automate documentation and reduce administrative workload (S. Y. Lin et al., 2019).

Several predictive use cases have emerged across diverse domains. In oncology, AI models using EHR data have shown promise in cancer diagnosis, tumor staging, treatment pattern recognition, and prognosis, particularly in cancers of the digestive and female organs. Deep learning and ensemble methods have gained popularity, achieving area under the curve (AUC) scores around 0.7, indicating moderate predictive performance (Yang et al., 2022). In

mental health, machine learning applied to EHRs has been used to detect general anxiety disorder (GAD) and major depressive disorder (MDD), which often go unnoticed in primary care. Early detection models can leverage biometric markers and patient characteristics to improve screening and triage processes (Nemesure et al., 2021)..

Despite these advances, AI-EMR integrations face considerable implementation challenges. Systems frequently suffer from poor interoperability, suboptimal user interfaces, and a lack of contextual sensitivity. These issues contribute to alert fatigue and user dissatisfaction, particularly when AI recommendations are irrelevant or difficult to interpret. Clinicians often report frustration when these systems fail to align with their workflow or local standards of care (Allen et al., 2024; Gomez-Cabello et al., 2024).

To address the need for transparency and clinician trust, explainable AI (xAI) systems have gained traction. For example, the xAI-EWS developed by (Lauritsen et al., 2020) offers not just a predictive score, but an explanation of the data inputs that led to it, bridging the interpretability gap and supporting clinical reasoning. In parallel, blockchain-integrated EMR systems are being explored for their ability to enhance data security and patient ownership. These systems employ AI techniques like optical character recognition (OCR) and NLP to summarize dispersed medical records into accessible, secure formats for emergency care (Chamola et al., 2023).

The importance of AI in EMR-based research is evident in global trends. A comparative study by (X. Chen et al., 2018) revealed a rapidly increasing number of AI-EMR publications from both the United States and China. While the U.S. leads in volume and academic impact, China has demonstrated stronger institutional and international collaborations. Despite this momentum, the study also highlights a fragmented landscape with varying research priorities across countries and a limited number of high-impact journals consistently publishing in this space.

Still, when compared to other areas, such as AI in imaging or standalone decision support systems, the literature on AI in EMRs remains relatively sparse. This gap signals an

opportunity for more focused, interdisciplinary research that examines real-world implementation, clinician acceptance, and the ethical implications of AI-augmented EMRs. Participatory co-design approaches and iterative user testing are increasingly advocated to ensure alignment with clinical needs and practice environments (Darcel et al., 2023).

2.2.2 Practical Applications and Future Potential

AI's role in primary care spans diagnostics, administrative efficiency, care coordination, and patient self-management. According to (S. Y. Lin et al., 2019b), the ten key areas where AI will transform primary care include risk prediction, population health management, chart documentation, diagnostics, and remote monitoring. For example, ambient AI scribes can assist in real-time documentation during consultations, freeing physicians from clerical burdens.

On the other hand, in a paper by (Allen et al., 2024) it has been found that while many primary care physicians (PCPs) are optimistic about AI, concerns remain regarding reimbursement, workflow changes, and the doctor–patient relationship. AI's ability to support chronic disease monitoring and patient triage is viewed positively, although concerns persist regarding the potential for AI to be used to justify increased panel sizes or reduce consultation time.

2.3 EMR Adoption in Primary Care

As briefly discussed in the previous chapter, EMR have increasingly become essential tools in primary care settings, offering digital alternatives to traditional paper-based records and improving provider-to-provider communication and care coordination (Manca, 2015; Tali, 2022). In Canada, EMR adoption rates have significantly risen, with certain jurisdictions, such as the Northwest Territories, achieving complete participation among primary care providers (Anderson et al., 2018). Despite high adoption rates, the full potential of EMRs often remains unrealized, as many healthcare providers primarily utilize basic features and neglect advanced functionalities. The efficacy of human-AI collaboration is not only a function of the accuracy of the underlying mathematical process behind the AI system

but also human factors, including trust. A holistic approach recognizing health care as a dynamic socio-technical system in which sub-elements interact with each other is necessary to understand trust relationships in human-AI collaboration. For instance, trust in AI systems might be affected by organizational policies, culture, specific tasks assigned to the health care providers, other similar computational tools used by the providers, providers' interaction with other individuals such as patients and other providers, as well as internal and external environmental factors. This viewpoint is consistent with and complementary to the research roadmaps proposed in the systems engineering literature on AI (Shachak et al., 2009). Applying human factors methodologies such as the SEIPS (Makam et al., 2014) to the health care domain can assist researchers in capturing the entire socio-technical work system. These holistic human factors models provide a useful conceptual framework for researchers to capture contemporary and dynamic issues relevant to trust modeling in healthcare (Rahal et al., 2021).

Research has highlighted varied outcomes associated with EMR implementation. While some studies have reported enhanced efficiency in administrative tasks such as billing, scheduling, and communication, satisfaction related to clinical functionalities, particularly mental health screenings, remains limited (Carbone et al., 2020). Issues such as inadequate training and lack of provider readiness to adopt more sophisticated EMR features frequently emerge as key barriers to optimal EMR utilization and overall satisfaction (Carbone et al., 2020; Rahal et al., 2021).

Moreover, usability concerns have been consistently identified as barriers to broader EMR acceptance among clinicians. Common issues include perceptions that EMRs are not patient-friendly during consultations, increased consultation duration, insufficient technical support, concerns about data migration, and inconveniences caused by system downtime (Cheung et al., 2013). These challenges underscore the need to address usability factors comprehensively when designing and implementing EMRs in primary care settings.

On the other hand, several additional factors have positively influenced PCPs' use of advanced EMR features, including physician motivation, user satisfaction, peer mentoring,

EMR experience, gender differences, physician perceptions, transition planning for roles and processes, team-based care, adequate technical support and training, shared resources, affiliation with integrated delivery systems, financial incentives, and supportive policy frameworks (Rahal et al., 2021). Furthermore, experiences with EMR usability vary significantly among healthcare professionals; doctors typically perceive technical quality, ease of information retrieval, and error prevention features more positively than nurses in primary care settings, while nurses in hospitals have a more favorable experience with EMRs regarding routine task support, learnability, and ease of patient data entry (Lloyd et al., 2021).

Additionally, clinicians' concerns about EMR accessibility, reliability, and utility negatively impact adoption, although many acknowledge EMRs' potential to enhance clinical productivity, patient safety, and care quality. Younger, technologically adept PCPs working in larger practices generally show more positive attitudes toward EMR usage compared to older, less tech-savvy counterparts operating in solo practices. Adequate training, transparent policies, and financial considerations, including start-up costs and ongoing maintenance, play significant roles in shaping EMR implementation outcomes (O'Donnell et al., 2018).

Primary care continues to face significant challenges despite its central role in managing healthcare costs, quality, access, and equity. This tension has prompted calls for a fundamental re-evaluation of practice structures, workflows, and the integration of technologies, such as EMRs, to meet the evolving demands of patients and society effectively (McMahon(Mcmahon et al., 2020). Evidence suggests that EMR implementation effectively reduces documentation errors and patient waiting times, improving overall system efficiency and quality of patient care (Albagmi et al., 2021).

Physician satisfaction with EMR systems has been high, especially regarding components like remote access and electronic messaging, which enhance communication efficiency and care delivery. However, certain features such as integrated online references were not deemed significantly advantageous compared to general web-based access (Joos et al., 2006).

Thus, while EMRs have transformed primary care practices considerably, understanding and addressing these varied factors

2.4 Human Factors in AI-augmented EMRs and CDSS

A growing body of literature examines the human factors impacting the integration of AI within EMRs and CDSS, focusing on usability, trust, workflow integration, and cognitive load.

In a mapping review by (Asan & Choudhury, 2021) across human factors journals identified only 48 studies on AI in healthcare over the prior decade, primarily emphasizing user perceptions, cognitive workload, trust, and usability. Strikingly, none of these studies evaluated AI tools embedded directly within real-world EMRs, revealing a significant gap in ecologically valid research. Instead, the majority of studies were simulation-based or examined clinician-AI interaction in isolation from actual workflow environments. Asan and Choudhury emphasized that human factors considerations, such as cognitive workload, explainability, interface usability, and workflow fit, were either inconsistently measured or entirely absent in many AI studies. They argued that the development and implementation of AI in clinical settings must go beyond technical performance, calling for interdisciplinary design teams that include human factors engineers from the outset. Their work underscores the importance of usability evaluation methods, such as cognitive walkthroughs and heuristic analyses, as essential tools to ensure that AI tools in EMRs are not only intelligent but also clinically meaningful, intuitive, and safe to use. This review has become a frequently cited cornerstone in positioning usability and clinician experience as central concerns in the successful adoption of AI in healthcare.

Furthermore, a narrative review by (Ye et al., 2024b), explores the integration of AI into Electronic Health Records (EHRs) with a strong emphasis on human factors. The review highlights key challenges such as usability limitations, alert fatigue, and workflow misalignment, which often hinder clinician acceptance of AI-enhanced tools. It notes that while AI holds promise for improving decision support, poor interface design and lack of

context-aware recommendations can disrupt clinical flow and increase cognitive burden. The authors advocate for user-centered development processes, stressing that AI systems should be co-designed with clinicians to ensure alignment with existing documentation practices and cognitive workflows. This review reinforces the importance of human factors engineering in achieving safe, interpretable, and actionable AI within EMRs.

2.4.1 Conceptual Frameworks for Clinician–AI Interaction

In a 2022 study, a framework grounded in Technology Acceptance and Expectancy Theories was proposed to analyze clinician–AI interactions, factoring in expectancy, workload, trust, cognitive capacity, and patient safety. It emphasizes measuring both qualitative and quantitative outcomes to improve adoption and accountability in EMR contexts (Choudhury, 2022b).

A usability study involving oncologists employed think-aloud protocols to assess explainable AI for lung cancer recurrence risk, concluding that developers must deeply understand end-user contexts to capture meaningful user experience feedback (Anjara et al., 2023). Furthermore, a 2025 survey on human-centered evaluations of XAI in CDSS catalogued existing methodologies and pinpointed gaps, ultimately proposing a structured evaluation framework aligned with clinical needs (Gambetti et al., 2025).

2.4.2 Cognitive Work in Clinical Settings

Understanding cognitive work within clinical environments is fundamental to enhancing clinical decision-making, patient safety, and healthcare quality. Clinical tasks often require complex cognitive processes, including perception, memory, judgment, and problem-solving, particularly in high-stakes, rapidly evolving contexts such as hospital operating rooms and intensive care units (Dawson, 1993; Nemeth et al., 2006).

2.4.3 Nature of Clinical Cognitive Tasks

Clinical decision-making relies heavily on intuitive and analytical judgments. Prediction, a core component of clinical cognition, is integral to diagnosing conditions, determining

prognoses, and selecting therapies, as well as planning monitoring intervals and preventative strategies (Dawson, 1993). Although clinicians frequently manage uncertainty due to variability in patient data and the complexity of medical conditions, their judgments are further complicated by cognitive limitations and methodological constraints inherent in clinical practice (Dawson, 1993). To address these challenges, research increasingly explores methods to effectively represent clinical data visually, thereby amplifying human cognition by leveraging perceptual capabilities (Effken et al., 2001).

2.4.4 Cognitive Work Analysis (CWA)

Among the cognitive frameworks, Cognitive Work Analysis (CWA) has been widely recognized as particularly suited for examining complex sociotechnical systems, including healthcare. CWA was introduced by Jens Rasmussen and colleagues in the 1980s as a formative, constraint-based framework for complex systems, later expanded into design guidance by Kim Vicente. The classic five-phase structure includes: Work Domain Analysis (WDA), Control Task Analysis (ConTA), Strategies Analysis, Social Organization Analysis, and Worker Competency Analysis, offering a comprehensive way to model cognitive work under varying constraints (Rasmussen et al., 1994). Vicente's 1999 text synthesizes earlier work into ecological interface design methods, providing a theoretical and practical foundation for interfaces that reflect and support natural work constraints (Vicente, 1999).

- **Work Domain Analysis (WDA)** identifies the underlying constraints, goals, and necessary information variables within a clinical workspace. It defines the fundamental purpose and constraints governing clinical tasks, serving as a foundation for subsequent analyses.
- **Control Task Analysis (ConTA)** outlines tasks necessary to fulfill system objectives without specifying exactly who or what performs these tasks.
- **Strategies Analysis (SA)** explores different cognitive strategies available for achieving these tasks, considering the cognitive load implications and resulting design requirements.

- **Social Organization and Cooperation Analysis (SOCA)** addresses how tasks are allocated among human and technological actors, highlighting necessary communication channels and coordination mechanisms within teams.
- **Competencies Analysis (CA)** identifies the cognitive skills required for tasks, distinguishing between effortless cognitive processes and cognitively demanding tasks, suggesting appropriate areas for decision-support integration or cognitive offloading through automation.

While not all five phases of CWA are necessary in every context, even partial application has demonstrated value. For example, (Jiancaro et al., 2014) reviewed applications of CWA in health informatics and emphasized its utility in aligning system design with the nuanced demands of clinical work. Similarly, (Effken et al., 2001) illustrated how CWA could be used to model and support nursing decision-making through better visual and cognitive support structures.

2.4.5 Applications and Limitations of CWA in Healthcare

A scoping review of CWA applications revealed significant interest and adoption primarily in acute care settings, notably for decision support, error investigation, and medical informatics. Despite its proven utility in acute settings, there remains a noticeable gap in applying CWA to community-based healthcare and organic social systems due to challenges in modeling human and biological system uncertainties (Jiancaro et al., 2014).

Opportunities exist for expanding the CWA framework, including developing auditory displays, innovative training applications, incident investigations, and enhancing inter-team workflows. However, the most substantial contribution of CWA remains its deep exploration into complex systems, facilitating an understanding of multidimensional problems inherent in healthcare environments. This, in turn, fosters more effective patient safety measures and improved clinical outcomes within complex sociotechnical contexts (Jiancaro et al., 2014).

More recent studies further demonstrate CWA's relevance to modern healthcare environments. (Ashoori et al., 2014) used Team CWA to explore communication and

coordination dynamics in a birthing unit, identifying how emergent and routine scenarios influence team structures. (Chin et al., 2018) applied Team CWA to evaluate physician–pharmacist collaboration in EMR-supported environments, uncovering system-level barriers that disrupted information flow despite shared platforms. (St-Maurice & Burns, 2017) employed Work Domain Analysis (WDA) to map treatment goals and environmental constraints in patient-centered care, offering a structured approach to guide interface and documentation tool design.

A paper by (Choudhury & Asan, 2023), quantitatively examined how cognitive workload and situation awareness influence clinician adoption of an AI-powered Clinical Decision Support System (CDSS). The study was conducted in a real-world setting at a U.S. academic medical center, where 119 clinicians had access to the Blood Utilization Calculator (BUC), an AI-CDSS tool embedded within the hospital’s electronic health record (EHR) system. The study utilized validated instruments to measure perceived cognitive workload (NASA-TLX), situation awareness (SA), and behavioral intention to adopt the AI-CDSS.

The results revealed that higher cognitive workload was negatively associated with clinicians' intention to use the system, suggesting that if the AI tool added mental strain or interfered with decision-making efficiency, its perceived usefulness declined. In contrast, higher levels of situation awareness were positively correlated with intention to use, indicating that when clinicians felt the system improved their understanding of the clinical scenario, their trust and willingness to engage with it increased.

This study provides compelling evidence that the adoption of AI in EMRs is not purely a function of algorithmic accuracy or availability of recommendations but is deeply influenced by human-centered variables such as mental effort and situational clarity. The authors highlight the need for AI-CDSS designs that support clinicians’ cognitive processes, rather than disrupt or overload them. Importantly, their findings argue for designing AI tools that enhance decision context and reduce ambiguity, rather than simply automate recommendations.

Furthermore, the study underscores the value of integrating human factors assessments into the evaluation and deployment of AI tools in healthcare, especially as CDSS functions become increasingly complex. Tools that fail to consider clinician cognitive load may unintentionally increase risk of error or non-adoption, even if their outputs are technically valid. The findings support the broader assertion that AI success in clinical environments depends not only on performance metrics, but also on how well the technology aligns with the clinician’s mental model and workflow.

2.5 Decision-Making in Clinical Settings

Clinical decision-making is a complex cognitive activity essential to healthcare practice, involving critical judgment, reasoning, and problem-solving. Clinicians integrate theoretical knowledge, patient information, experiential insights, and contextual factors to form clinical judgments regarding diagnosis, treatment, and patient care (Croskerry, 2005; Dawson, 1993; Smith et al., 2008).

In recent years, increasing attention has been paid to the cognitive vulnerabilities that affect decision quality, particularly the influence of heuristics and biases, such as confirmation bias and anchoring, which can contribute to diagnostic error even in experienced clinicians (Croskerry et al., 2013; Saposnik et al., 2016). At the same time, growing interest in clinical decision support systems and AI –enabled tools, have been introduced to assist clinicians in real-time decision-making. While these systems offer potential benefits, such as reducing variability and improving diagnostic accuracy, they also introduce new challenges related to workflow integration, cognitive overload, and human–AI trust calibration (Shortliffe & Sepúlveda, 2018; Sutton et al., 2020).

2.5.1 Models and Approaches to Clinical Decision-Making

Historically, clinical decision-making literature has recognized two predominant theoretical models: the information-processing model and the intuitive-humanist model (Banning, 2008). The information-processing model emphasizes structured, analytical reasoning, characterized by the generation and testing of hypotheses. In contrast, the intuitive-humanist

model is rapid, heuristic-driven, and experience-based, facilitating quick judgments that are particularly common among experienced clinicians (Banning, 2008; Dawson, 1993).

Afterwards, a third multidimensional model has emerged, integrating aspects of both analytical and intuitive approaches while placing significant emphasis on patient-specific elements critical for cue recognition and decision accuracy (Banning, 2008). This hybrid model, proposed initially for nursing, suggests that clinicians dynamically switch between reasoning modes based on clinical complexity and their experience. Experienced practitioners, in particular, may use all three approaches interchangeably or concurrently, benefiting from enhanced saliency and nuanced pattern recognition developed over time.

While much early literature focused on these distinct frameworks, more recent work has underscored a fluid interplay between them, shaped by case complexity, time constraints, and cognitive workload. Ethnographic studies in urgent care teams revealed expert clinicians combine intuitive patterns matching with analytical evaluation, testing rapid solutions against rational benchmarks in real time (Irvine et al., 2025).

Newer hybrid models argue that clinical reasoning cannot be understood in isolation, it is inherently contextual and adaptively modulates across cases. For instance, Iranian ICU nursing studies during COVID-19 found clinicians using intuition under crisis conditions, supported by holistic awareness and situational judgment (Aghajani et al., 2021).

2.5.2 Cognitive Dimensions of Clinical Decision-Making

Clinical decision-making operates along a cognitive continuum ranging from intuitive, informal judgments to analytical, calculated decisions, depending on task complexity and uncertainty levels (Dawson, 1993). Research done by (Norman, 2000), emphasizes that effective clinical decision-making requires matching the cognitive approach to the clinical task, noting considerable variability across clinical settings. For instance, dermatology clinics often face tasks with lower uncertainty, favoring intuitive judgments based on pattern recognition, whereas trauma units encounter higher uncertainty and complexity, necessitating a more analytical approach (Croskerry, 2005).

Another research done by (Pelaccia et al., 2017), highlight the significance of understanding cognitive processes behind diagnostic and therapeutic decisions, particularly within emergency medicine, aa setting characterized by rapid decision-making, high cognitive load, and substantial diagnostic uncertainty. Here, decision-making errors frequently occur, underscoring the importance of investigating cognitive reasoning processes to improve clinical outcomes.

A 2025 scoping review identified 28 distinct cognitive biases, including anchoring, confirmation bias, availability bias, and premature closure, that affect decision-making in high-pressure prehospital and in-hospital critical care. Common contributing factors included time pressure, social influences, and lack of unbiased feedback (Awanzo & Thompson, 2025). A 2025 Frontiers study experimentally examined the interaction between cognitive load and dual-process reasoning, showing that increased cognitive load led to greater reliance on heuristics, especially for emotionally positive outcomes (Zucchelli et al., 2025).

Lastly, investigations using real-time cognitive load measurement in emergency department residents showed significant and fluctuating cognitive demands, with critical events triggering notable stress and resource depletion, highlighting the need for decision support systems that adapt to workload variation (Appelboom et al., 2025).

2.5.3 Contextual Influences on Clinical Decision-Making

The clinical decision-making process cannot be separated from the context in which it occurs. Context includes environmental factors (hospital, private practice, emergency departments), situational aspects (scheduled appointments versus emergencies), and resource availability (time constraints, support staff, medical equipment), all profoundly affecting clinicians' cognitive processing (Charlin et al., 2012; Croskerry, 2000; Pelaccia et al., 2017). Situated cognition theories further explain how clinicians utilize environmental cues and resources to adapt their decision-making processes to specific clinical contexts, significantly affecting diagnostic and therapeutic judgments (S. J. Durning et al., 2010; Pelaccia et al., 2017). The emergency medicine setting exemplifies this concept, where clinicians must

rapidly assess multiple patients, manage substantial uncertainty, and make immediate therapeutic decisions under pressure, highlighting the integral role of context in shaping clinical reasoning (Pelaccia et al., 2017). An experimental 2020 study found that added “irrelevant” contextual details disrupted diagnostic accuracy and increased clinician-reported cognitive load (S. J. Durning et al., 2012). Moreover, a 2022 study in Japanese EDs quantified that overconfidence (22.5%), confirmation bias (21.2%), and anchoring (11.4%) were common sources of error, further accentuated during night shifts (Kunitomo et al., 2022).

Recent theoretical work has evolved beyond viewing context as a “noise” factor and instead conceptualizes it hierarchically. A 2023 framework proposed a micro–meso–macro model, where context ranges from immediate patient–clinician interactions to broader organizational and policy influences, offering opportunities to enhance decision-making through active leveraging of context (Choi & Durning, 2023).

A recent scoping review (2025) identified nearly 1,000 context factors, ranging from patient demographics and family dynamics to institutional policies and disease complexity, categorizing them into six domains: patient, clinician, family, illness/treatment characteristics, colleagues, and institutional factors. The study emphasizes that contextual mismatch in CDSS can reduce adoption and effectiveness (Schuler et al., 2025).

2.5.4 Methodologies for Investigating Clinical Reasoning

To better capture the complexity and nuance of clinical reasoning, qualitative research methodologies have gained increasing acceptance. Such methods, including think-aloud protocols, retrospective protocols, and ethnographic observations, allow researchers to examine decision-making in realistic or near-realistic clinical environments, thus preserving the richness and contextual specificity inherent in clinical reasoning (Pelaccia et al., 2017; Smith et al., 2008). A recent 2023 study involving emergency medicine residents demonstrated how adaptive expertise and epistemic distance shape decision making in high-pressure clinical encounters (Obucina et al., 2023). Similarly, pharmacy practice research in

2023 used think-aloud methods to clarify how pharmacists reason about medication safety (Duong et al., 2023).

Criticism of purely quantitative, controlled experimental approaches to clinical reasoning highlights their limited capacity to account for real-world complexity and situational factors (Croskerry & Tait, 2013; Pelaccia et al., 2017). Consequently, ethnographic methods and naturalistic studies have been proposed as more effective approaches to understanding decision-making in actual clinical settings, encompassing the practical constraints and environmental influences clinicians face daily (S. Durning et al., 2011; Pelaccia et al., 2017). A 2024 qualitative study in emergency settings revealed the workflow's influence on decisions, especially during high-uncertainty situations like pneumonia triage (Taber et al., 2024).

These qualitative approaches address the limitations of purely quantitative designs, such as controlled experiments and surveys, that fail to capture domain complexity and situational variability. They enable researchers to unpack how clinicians navigate uncertainty, balance reflective and reflexive reasoning, and leverage environmental cues for real-time decisions.

2.5.5 Decision-Making and Patient Interaction

Effective clinical decision-making extends beyond clinician cognition, involving active patient engagement and informed decision-making processes. (Braddock et al., 1997), in their analysis of outpatient settings, clinicians frequently described decisions superficially, often omitting discussions about risks, benefits, and alternative treatments. Notably, clinicians rarely assessed patient understanding or explicitly elicited patient preferences. These findings underscore the importance of a shared decision-making framework, emphasizing transparent communication and patient involvement to improve healthcare outcomes and patient satisfaction.

A large-scale 2024 scoping review found that SDM improves patient adherence and satisfaction, even in populations with complex care needs, although barriers persist, particularly among those with multimorbidity or cognitive impairment (Perron et al., 2024).

2.5.6 Enhancing Clinical Decision-Making Capabilities

To improve clinical decision-making quality, various strategies have been proposed. (Smith et al., 2008), emphasize ongoing professional education, reflective practices, and cognitive debiasing techniques to help clinicians recognize and mitigate common cognitive errors such as confirmation bias, anchoring, and premature closure (Croskerry, 2005; Dawson, 1993).

Furthermore, effective use of Clinical Decision Support Systems (CDSS), which have been discussed earlier, structured clinical pathways, and collaborative multidisciplinary teamwork have been recommended to enhance decision accuracy and reduce cognitive burden, particularly in high-complexity clinical settings (Gomez-Cabello et al., 2024; Lauritsen et al., 2020). Another multi-center study in Hong Kong (2025) showed that trust in doctors significantly increased inpatient participation in SDM, while outpatient involvement varied based on clinician–patient dynamics and patient demographics (Tian et al., 2025).

The integration of SDM tools into EHRs appears promising: a 2025 systematic review identified 18 such tools, 94% of which demonstrated improved SDM uptake, particularly when tools were well integrated into workflow and backed by decision-aid frameworks (Pierce et al., 2025). Furthermore, patient-reported outcomes underscore the relational dimension of SDM. The same systematic review by (Perron et al., 2024) reported that involving patients via SDM strengthens trust, communication, and the therapeutic alliance, even when interventions do not directly improve clinical metrics.

2.6 Clinicians' Perception of AI

As AI technologies, including machine learning and generative AI, increasingly integrate into clinical settings, understanding clinicians' perceptions, trust, and acceptance of AI is critical to successful adoption and utilization in healthcare workflows. This section synthesizes the literature regarding clinicians' attitudes toward AI, highlighting factors influencing acceptance, trust, perceived risks, and the implications for clinical practice.

2.6.1 Trust and Acceptance of AI in Clinical Settings

Central to clinician perception of AI is trust, which significantly influences acceptance and willingness to use AI systems. Trust in AI is primarily shaped by clinicians' perceptions of AI's trustworthiness, encompassing information credibility, application reliability, and perceived value (Manuscript & Diego, 2022; Stevens & Stetson, 2023). The TrAAIT model developed by (Stevens & Stetson, 2023) highlights information credibility (quality, accuracy), system performance (reliability, adaptability), and application value (usefulness, ease of use) as core determinants of trust. Trust notably explains a significant portion of clinician acceptance (56%) and their ongoing general stance towards AI (36%), moderated by organizational assurances, clinician experience, and age (Stevens & Stetson, 2023).

The research done by (Perivolaris et al., 2024) identified additional interaction traits affecting clinician-AI relationships, including ease of use, usability, satisfaction, communication quality, ethical and professional concerns, and workflow impact. Clinicians' acceptance or skepticism hinges on AI's perceived usefulness, reliability, and capacity to integrate smoothly into existing clinical workflows without excessive disruptions.

2.6.2 Impact of Demographics and Personality Traits

Clinician demographics and individual characteristics significantly shape AI perceptions. Younger and more educated clinicians tend to have more confidence and exhibit more favorable attitudes toward AI-assisted interpretations compared to older colleagues (York et al., 2020). Additionally, clinicians who perceive AI as reducing workload exhibit higher trust levels and acceptance rates. Conversely, clinicians apprehensive about AI-related risks show reluctance towards integrating AI into decision-making processes (Shamszare & Choudhury, 2023).

The research done by (Kauttonen et al., 2025) highlighted that personality traits also influence AI acceptance, where clinicians with more flexible, less organized personalities exhibited generally more positive attitudes toward AI. Interestingly, an inverted U-shaped relationship exists between AI acceptance and self-reported AI knowledge; moderate

familiarity with AI correlates with optimal acceptance, whereas low or overly high self-reported knowledge correlates negatively.

2.6.3 Contextual and Ethical Considerations

Clinicians' perceptions of AI are heavily influenced by contextual factors including institutional settings, organizational culture, legal implications, and patient care scenarios. Ethical considerations, such as data privacy, accountability, transparency, fairness, and equity, further shape attitudes and acceptance toward AI implementation (Alanazi, 2023; Shevtsova et al., 2024). Concerns about medical responsibility are particularly salient; clinicians express apprehension regarding accountability for AI-driven decisions that deviate from established clinical standards, thereby affecting trust and adoption (Asan et al., 2020).

The research done by (Darcel et al., 2023) introduced the “window of humane technology” concept, suggesting that optimal AI implementation occurs when AI augments, rather than replaces, human capabilities. They advocate for participatory co-design and human-centered approaches, underscoring the necessity of maintaining clinician autonomy and addressing equity considerations to foster trust and ethical AI integration.

2.6.4 Decision-Making Dynamics and AI Interactions

Clinicians do not uniformly accept AI recommendations; instead, their decision-making involves nuanced interactions with AI systems. In the research done by (Sivaraman et al., 2023), they identified four distinct clinician behaviors regarding AI recommendations: “Ignore,” “Negotiate,” “Consider,” and “Rely.” The most common behavior, negotiation, involves selectively accepting aspects of AI-generated recommendations based on clinical judgment and patient-specific factors, reflecting complex decision-making dynamics rather than simple binary acceptance or rejection.

Further research indicates that while clinicians often find explanatory AI visualizations useful, enhancing their decision-making confidence, such visualizations do not necessarily increase binary concordance with AI recommendations. This complex interplay underscores

the need to design AI systems adaptable to varied clinician preferences and clinical scenarios (Sivaraman et al., 2023).

2.6.5 Balancing Trust and Skepticism: Optimal Trust Concept

Asan et al. (2020) propose the concept of optimal trust, emphasizing that overly high trust can lead clinicians to uncritically accept AI outputs, potentially leading to significant adverse outcomes in critical care scenarios. An optimal trust level requires balanced skepticism, wherein clinicians recognize both AI capabilities and limitations, engaging in critical evaluation of recommendations, especially in life-critical applications (Asan et al., 2020).

Clinicians emphasize that human-AI collaboration effectiveness depends not only on AI accuracy but also on human factors, including organizational policies, clinician-AI interactions, and external environmental influences (Asan et al., 2020). Hence, successful AI implementation requires holistic human factors methodologies, considering healthcare as dynamic sociotechnical systems where multiple sub-elements influence AI trust and acceptance.

2.6.6 Strategic Implementation and Adoption Approaches

Clinicians generally support AI integration strategies that complement existing clinical workflows rather than disrupt them. (Shamszare & Choudhury, 2023) advocate parallel integration strategies, highlighting potential pitfalls of sequential AI integration, which may inadvertently increase clinician workload and skepticism. They recommend presenting AI explicitly as supportive tools to enhance clinician skills and streamline workflows.

Additionally, factors influencing clinicians' intent to use AI systems, including performance expectancy, perceived risk, and technology perceptions, require attention from AI developers and healthcare managers. Clearly communicating AI benefits, ease of use, and potential to positively impact patient outcomes significantly reduces perceived risk and enhances clinician acceptance (Choudhury, 2022).

2.6.7 Shared Decision-Making

Clinician adoption is further reinforced when AI technologies effectively support shared decision-making (SDM), fostering greater patient engagement, confidence, and satisfaction. AI decision aids that deliver tailored, individualized information promote positive clinician-patient communication and trust (Hassan et al., 2021). However, clinicians note barriers to SDM-related AI implementation, including variability in patient technology literacy and incomplete or inaccurate data inputs.

In conclusion, successful AI integration into healthcare demands comprehensive understanding and active management of clinician perceptions, trust dynamics, ethical considerations, and practical decision-making interactions. Engaging clinicians in participatory design, clearly addressing ethical and legal implications, and developing balanced, context-sensitive AI solutions are essential strategies to realize AI's full potential in healthcare.

This chapter has explored key areas relevant to the integration of AI into EMRs within primary care settings, highlighting EMR adoption, cognitive workflows, clinical decision-making processes, user-centered design principles, and clinicians' perceptions and trust in AI systems. While EMRs have significantly evolved and become integral in primary care, the effective integration of AI presents unique challenges and opportunities related to cognitive load, decision accuracy, user acceptance, and ethical considerations. Clinician trust, shaped by AI reliability, transparency, and contextual fit, emerges as a critical determinant of successful AI adoption. Despite substantial research efforts, notable gaps remain, particularly in understanding how clinicians dynamically negotiate AI recommendations across varying clinical complexities. Addressing these gaps through empirical investigation is essential to ensuring AI technologies complement rather than complicate clinical workflows. Subsequent chapters of this thesis will build upon these insights, detailing methodologies employed, presenting empirical findings, and discussing their implications for primary care practice and AI integration strategies.

Chapter 3

Methodology

This chapter outlines the methodological foundations underpinning the thesis and describes the sources of empirical data used in this research. The study design, recruitment strategy, interview guide, and primary data collection procedures were developed and conducted by my colleague, Krizia Francisco, under the supervision of Professor Catherine M. Burns in *JMIR Research Protocols* (vol. 13, e54365). That publication, hereafter referred to as “the Francisco & Burns protocol”, established a user-centered, qualitative approach aimed at understanding how Canadian primary care clinicians might adopt an AI-enabled electronic medical record encounter (K. M. Francisco & Burns, 2024).

All interviews, transcripts, and field notes originate from the Francisco & Burns protocol. My contribution begins after data collection: I conduct a secondary qualitative analysis that (i) augments the original thematic coding with decision-ladder mapping to capture clinicians’ cognitive processes, and (ii) deepens the content analysis to surface nuanced information needs. The practical design implications that emerge from this extended analysis are noted briefly in the Discussion chapter; however, unlike the protocol, generating an exhaustive set of interface requirements is outside the primary scope of my methodological work.

3.1 Data Collection and Study Design

The methodological approach used in this research is contextual design. As mentioned earlier in the literature review chapter, User-centered design (UCD) is a methodological framework that emphasizes deeply understanding users, their tasks, needs, motivations, and operational contexts, to inform the development of effective and intuitive solutions (Norman, D.A., 2002). Contextual design follows a user-centered design philosophy, where an extensive understanding of user tasks, motivations, intents, strategies, and detailed operational steps drives innovation (Holtzblatt & Beyer, 2016). The adoption of contextual and user-centered design methodologies benefits research and development processes by ensuring alignment

between user expectations, needs, and final system functionalities, thus facilitating higher adoption rates, improved user satisfaction, and reduced implementation barriers(Endsley & Jones, 2016; Norman, D.A., 2002). As mentioned, this approach was originally detailed in the published protocol (K. M. Francisco & Burns, 2024).

A collaborative partnership was established with TELUS Health to facilitate comprehensive user-centered research, leveraging their cloud-based EMR platform known as the Collaborative Health Record (CHR). The CHR includes standard EMR functionalities such as cumulative patient profiles, free-text charting, customizable forms, and electronic scheduling. Additionally, it provides advanced features, including integrated virtual care capabilities, streamlined clinical encounters, and real-time clinical and business intelligence (K. M. Francisco & Burns, 2024).

Semi-structured, individual interviews were conducted to ensure consistency through standardized scenarios while allowing flexibility through targeted follow-up questions. Semi-structured interviews are a qualitative research method characterized by a pre-defined set of open-ended questions combined with the flexibility for interviewers to explore emerging themes through targeted follow-up questions (Kvale & Brinkmann, 2009). This method provides balanced and purposeful dialogue, ensuring valuable insights directly applicable to design considerations (Patton, 2014). Such flexibility is particularly beneficial in exploratory studies focused on understanding user workflows, decision-making processes, and interactions with complex technologies, making semi-structured interviews ideal for generating rich, context-sensitive insights critical for user-centered design considerations (Holtzblatt & Beyer, 2016).

The core objective of these interviews was to elucidate clinicians' decision-making processes during patient interactions, particularly identifying critical workflow components such as documentation timing and screen distractions. Given the diversity of primary care clinical presentations, specific, generalizable scenarios were selected to align closely with typical primary care workflows. The CHR's "Encounter" module was selected as the focal point, being central to clinical documentation and capturing comprehensive patient

interaction details, including questionnaires, health histories, clinical assessments, prescriptions, referrals, and follow-up actions (K. M. Francisco & Burns, 2024). Furthermore, pre-read material on AI and its capabilities in Canadian primary care was developed for the primary care clinicians to review before the interviews.

- **Part 1: Current Workflow (30 minutes)**

Initially, clinicians were asked to describe their existing workflow using their current EMR setup through two scenarios presented initially in the protocol (K. M. Francisco & Burns, 2024). Figure 3-1 Shows the current structure of the Encounter module within the CHR.

- **Scenario 1 (Mental Health):** Taylor Jones, a 29-year-old female patient, scheduled an appointment due to severe anxiety, identified through a pre-visit GAD-7¹ Questionnaire score (>15). This patient is now sitting in your office and this encounter screen is open on your screen, what flow would you engage in with the following screen? (e.g., which sections would you expand first, what would you chart, and what are the questions you ask next)?
- **Scenario 2 (Urinary Tract Infection - UTI):** Alice Smith, a 48-year-old female patient, presented with symptoms suggestive of a UTI, her previous antibiotic prescription dating back over two years. The patient is now sitting in your office with this encounter screen open on your screen. What flow would you engage in with the following screen? (e.g., which sections would you expand first, what would you chart, and what are the questions you ask next)?

¹ GAD7: Generalized Anxiety Disorder-7 Scale.

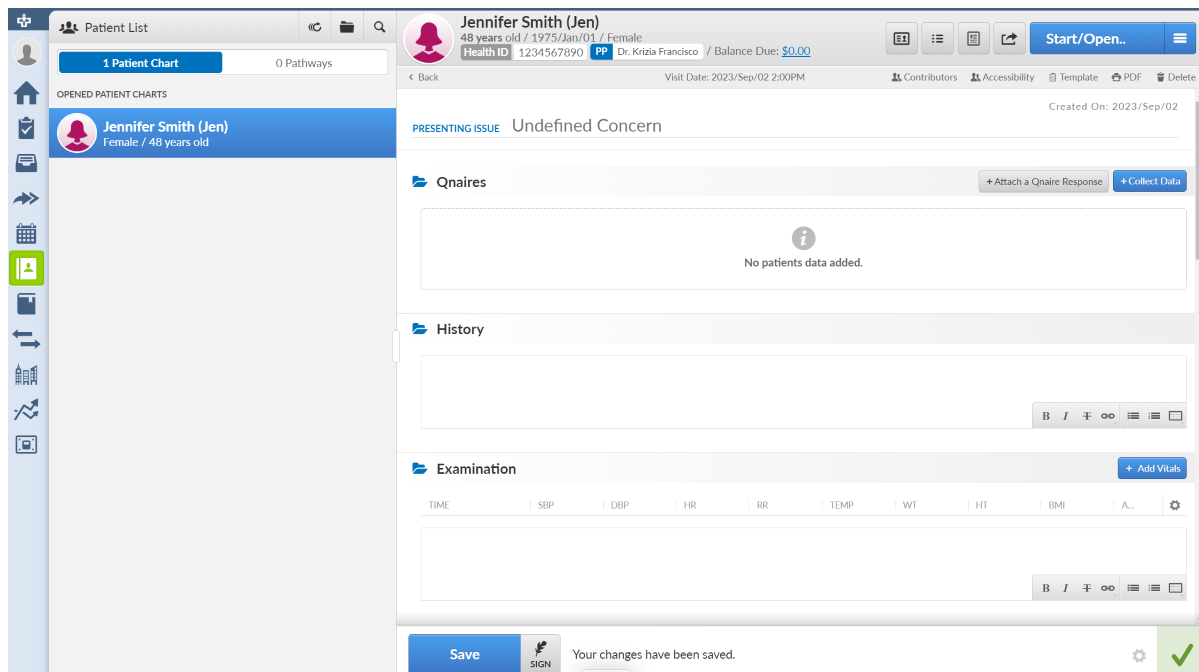


Figure 3-1 The encounter module in the TELUS CHR in an empty state

- **Part 2: AI-Enhanced Workflow (30 minutes)**

In the second phase of the interview, clinicians revisited the initial scenarios, this time interacting with an AI-enhanced version of the CHR encounter module (scenario 3 and scenario 4). The goal was to examine whether and how AI integration influences clinical workflows. Figure 3-2 shows an example of the mock-up shown to primary care clinicians, demonstrating an AI-enabled version of the encounter module in the CHR.

- **Scenario 3 (Mental Health):** Taylor Jones, a female patient aged 29, called your office 2 weeks ago requesting a visit related to her mental health. In preparation for her appointment, she was given a GAD7 to fill out at home; the results were then sent to your office, with a score of >15, indicating severe anxiety. Your EMR is now supported by AI, and before the patient’s appointment, it processes the results and prepopulates your encounter. This patient is now sitting in your office, and the encounter screen is open on your

screen. What flow would you engage in with the following screen? (e.g., which sections would you expand first, what would you chart, and what are the questions you ask next).

- **Scenario 4 (Urinary Tract Infection - UTI):** Alice Smith, a female patient aged 48, called your office with a suspected UTI. The last time she was prescribed an antibiotic for a UTI was over 2 years ago. AI now supports your EMR, and before the patient's appointment, it processes the results and prepopulates your encounter. The patient is now sitting in your office with this encounter screen open on your screen. What flow would you engage in with the following screen? (eg., which sections would you expand first, what would you chart, and what are the questions you ask next)

Specific differences introduced in this AI-enhanced interface included (K. M. Francisco & Burns, 2024):

- **Numeric confidence scores:** Presented ambiguously, clinicians discussed their assumptions regarding these scores, exploring their potential basis (e.g., large language models, best practices, or organizational data).
- **Actionable options (“approve, edit, decline”):** This feature aimed to explore clinicians' preferences regarding liability, transparency, and interaction with AI-generated suggestions, particularly regarding editing, approving, or declining AI recommendations.
- **Underlined actionable steps:** By highlighting tasks such as medication selection, this design probed clinicians' perceptions of the appropriateness and boundaries of AI's clinical recommendations.

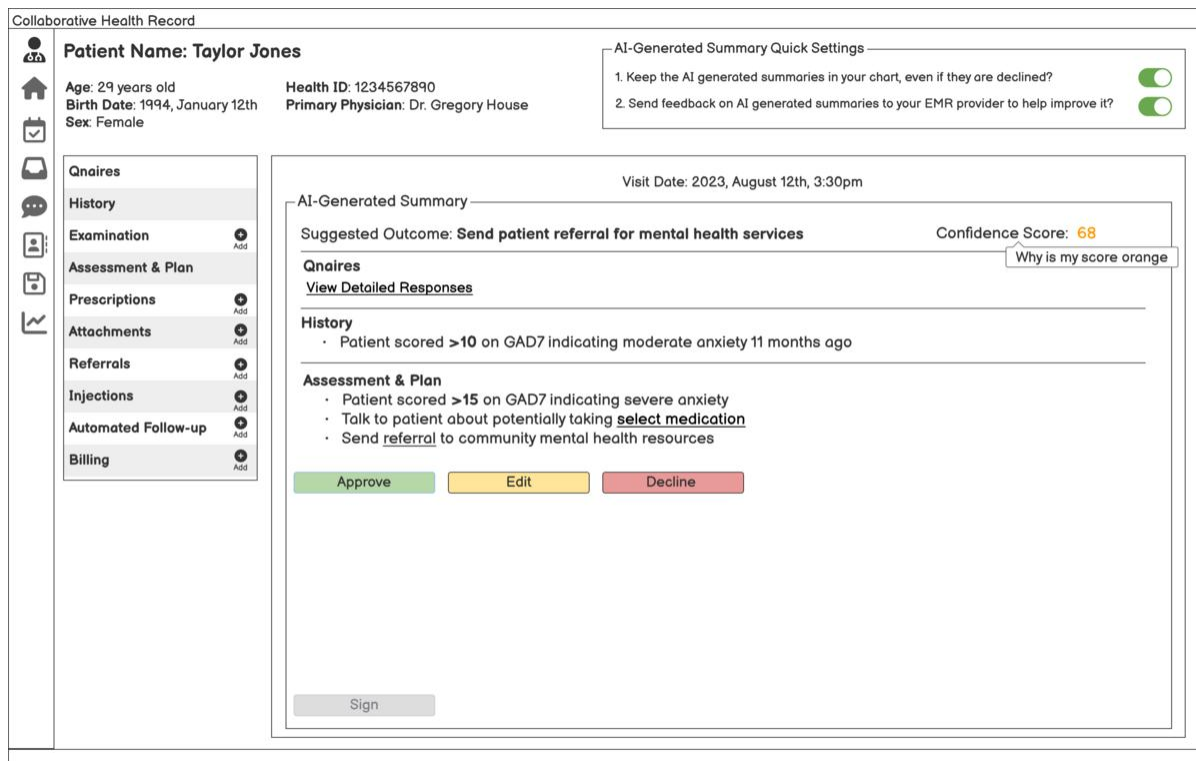


Figure 3-2 The AI-enabled version of the encounter in the CHR, shown to clinicians during part 2 of the first interview

3.1.1 Participant Recruitment and Demographics

Participants were recruited using targeted communications directed toward established primary care networks, including primary care digital health networks and the Association for Family Health Teams. Additionally, direct recruitment was conducted through emails and social media platforms such as LinkedIn. Inclusion criteria required participants to be primary care clinicians actively practicing within Ontario, Canada (K. M. Francisco & Burns, 2024). Each participant received a one-time honorarium of \$75 (VISA gift card) in appreciation for their participation and valuable insights (K. M. Francisco & Burns, 2024).

3.1.2 Ethical Considerations & Data Privacy

The study protocol was reviewed and granted ethics clearance by the University of Waterloo Research Ethics Board (REB #43922). Formal written and oral consent procedures were

administered to ensure participants were fully informed about the study's scope, confidentiality assurances, and data handling procedures. Participants were explicitly informed that interview transcripts would be recorded and securely stored on an encrypted hard drive for seven years, consistent with the University of Waterloo's guidelines for data retention (K. M. Francisco & Burns, 2024).

3.2 Data Analysis Methods

The data analysis phase of this research employed a mixed-methods approach, integrating qualitative analysis techniques within a cognitive decision-making (CDM) framework. Specifically, the qualitative data derived from semi-structured interviews were analyzed using decision ladder modeling and content analysis, combined to offer a comprehensive view of clinicians' decision-making processes and their interaction with the AI-enhanced EMR system.

The Decision Ladder (DL), conceptualized initially by (Rasmussen, 1986), provides a structured representation of cognitive activities involved in decision-making tasks. It systematically captures clinicians' sequential steps to evaluate patient data, identify clinical problems, consider potential interventions, and execute decisions. Utilizing the DL framework in this research enabled a clear visualization and understanding of clinicians' cognitive pathways, decision points, and information requirements during their interaction with both traditional and AI-supported EMR systems (Vicente, 1999).

Additionally, content analysis was employed as a complementary qualitative method, providing a systematic approach for coding, categorizing, and interpreting narrative data to identify themes, patterns, and insights relevant to the research objectives (Hsieh & Shannon, 2005).

Combining these methods provided a richer, multi-dimensional understanding of primary care clinicians' cognitive processes and user needs, facilitating a holistic interpretation of qualitative data and ensuring robust, triangulated findings (Creswell & Clark, 2017). Detailed

descriptions of each analytic method, including coding protocols and modeling procedures, are presented in the subsequent sections.

3.2.1 Decision Ladder Analysis

The decision ladder analysis methodology used in this research followed a structured cognitive decision-making framework outlined by (Rasmussen, 1986) and (Vicente, 1999). Decision ladders provide a visual and structured representation of cognitive decision-making, specifically capturing the processes and knowledge states involved when clinicians interact with the EMR system.

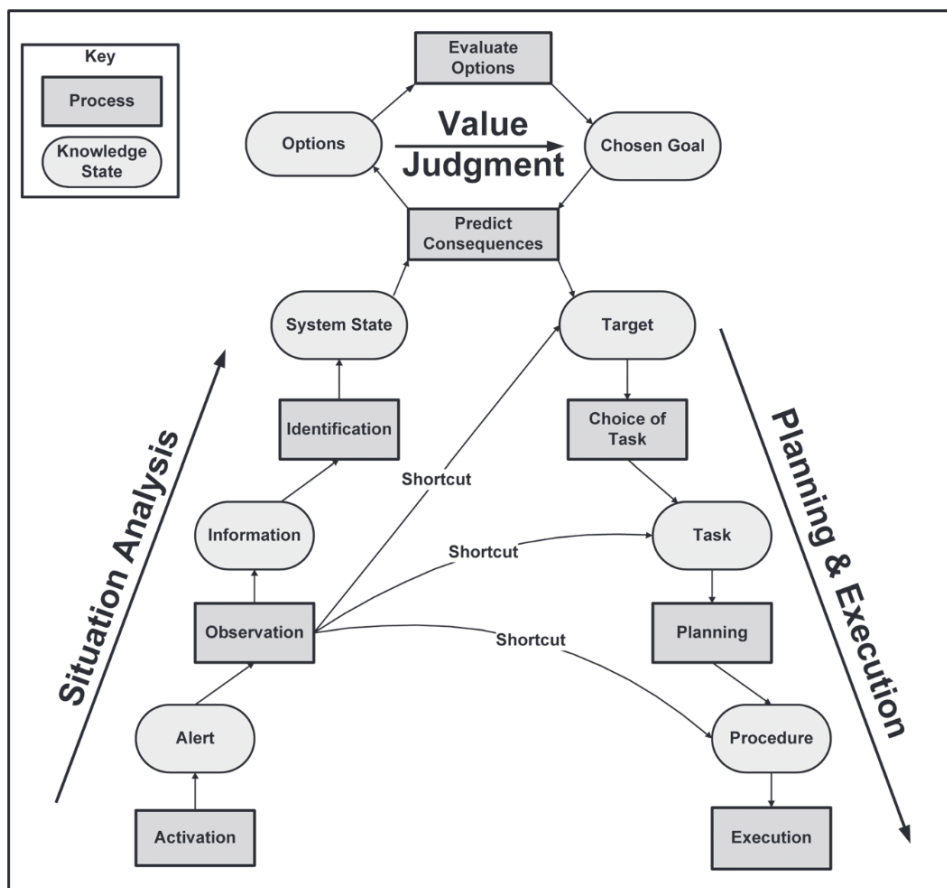


Figure 3-3 Decision ladder template

It's noteworthy that, in this thesis, the clinician's decision-making process is treated as the "system" modeled by the Decision Ladder. System states represent phases of clinical reasoning (e.g., problem identification, option generation, treatment selection). Patient presentations, EMR data, and AI outputs are considered as external inputs and contextual influences that shape transitions between states. This is to emphasize that while healthcare is inherently sociotechnical, the DL in this study is focused on capturing the cognitive trajectory of the clinician as the central decision-maker.

To perform this analysis, interview transcripts were reviewed for all four scenarios. A predefined coding scheme based on the decision ladder framework was utilized, comprising two main categories: knowledge states and processes. Knowledge states refer to the specific information, artifacts, or factual elements clinicians relied upon, including:

- Alert
- Information
- System State
- Options
- Chosen Goal
- Target State
- Task
- Procedure

The process codes corresponded to clinicians' descriptions of their cognitive steps or actions during decision-making, including:

- Activation
- Observation
- Identification

- Predict Consequences
- Evaluate Options
- Choice of Task
- Planning
- Execution

Using this scheme, relevant segments of the interview transcripts were systematically categorized according to these predefined decision ladder codes. In practice, transcript segments in which clinicians described their cognitive steps, judgments, or actions were coded under process, while segments describing specific information points or data referenced during decision-making were coded under knowledge states.

Additionally, special cognitive strategies known as “shortcuts,” specifically shunts (where intermediate steps are skipped, moving directly from one knowledge state to another) and leaps (direct transitions between non-adjacent process states), were identified and captured. These shortcuts signify clinicians' familiarity and experience, representing intuitive or expert-level decision-making processes (Vicente, 1999). In applying the DL, shortcuts were coded according to a consistent framework. A shunt was defined as a shortcut that connects an information-processing activity (box) to a state of knowledge (circle), bypassing some steps in the process. A leap was defined as a shortcut that directly connects one state of knowledge to another, bypassing multiple information-processing activities. To ensure coding consistency, leaps were further differentiated according to whether they ended at the Target stage (representing a direct transition to an overarching goal) or the Task stage (representing a direct transition to a specific action). This approach reflects guidance from prior DL applications, which emphasize the importance of defining consistent coding rules when shortcuts could plausibly be drawn toward multiple knowledge states.

To enhance the reliability of the coding process, an undergraduate research assistant independently reviewed the decision ladder codes and interview transcripts for all four

scenarios. This independent review helped to verify coding accuracy and ensure consistency across scenarios.

Following the coding, the extracted data were synthesized into visual decision ladder models, illustrating the clinicians' cognitive pathways for each scenario. These visualizations allowed for a detailed comparison between traditional EMR encounters and AI-enabled encounters, highlighting changes in workflow, information use, and decision strategies.

3.2.2 Shortcut Frequency Coding

In addition to mapping clinician decision-making pathways using the decision ladder (DL), the study also sought to capture the *approximate frequency* of shortcut use (shunts and leaps) across scenarios. This was pursued to provide insight into not only the *possibility* of shortcuts, but also their *tendencies of occurrence* in practice.

Following the completion of interviews, the transcripts were revisited to identify instances where participants described relying on shortcuts. A coding approach was applied to extract these frequencies:

- **Unit of analysis:** Each mention of bypassing or expediting decision steps (e.g., “I usually go straight to prescribing in these cases”).
- **Coding categories:** Shunts (direct connection between information-processing activity and knowledge state) and Leaps (direct connection between knowledge states, bypassing multiple steps), as defined in this study's framework.
- **Frequency estimation:** Counts were aggregated at the participant level. If a clinician described a shortcut as part of their *typical practice*, it was coded as a single occurrence for that shortcut type in that scenario.
- **Interpretation note:** Since clinicians often described decision-making in narrative terms rather than discrete steps, frequencies represent *approximate estimates* rather than exact tallies. Some shortcuts were explicitly described, while others were inferred from consistent patterns in practice.

This analysis allowed for exploratory insight into the relative prevalence of shortcuts across scenarios, while acknowledging that more precise quantification would require direct observation or EMR interaction data.

3.2.3 Content Analysis

In addition to decision ladder modeling, a qualitative content analysis was conducted to holistically capture clinicians' perspectives across all four interview scenarios. The goal of this analysis was to explore deeper patterns in clinical decision-making, particularly focusing on differences between existing workflows and AI-integrated workflows.

The content analysis was approached systematically in three stages, following an inductive-deductive hybrid approach (Hsieh & Shannon, 2005):

- 1. Initial Coding:** In the first stage, all interview transcripts across scenarios 1 to 4 were thoroughly reviewed, extracting meaningful segments and assigning initial descriptive codes. These codes captured key concepts, actions, perceptions, and user experiences articulated by the clinicians.
- 2. Categorization:** In the second stage, emergent patterns among the codes were identified, and related codes were grouped into broader categories and sub-categories. This process allowed underlying thematic structures within the data to emerge, such as differences in cognitive workload, perceived usability, trust in AI outputs, and workflow disruptions.
- 3. Refinement and Organization:** In the final stage, all categories and sub-categories were systematically reviewed, consolidated, and refined. Redundant codes were merged, and ambiguous categories were clarified to ensure internal coherence and meaningful thematic distinctions.

Importantly, because one of the research objectives was to understand decision-making across different complexity levels, the content analysis compared scenarios 1 and 2 (representing the clinicians' existing EMR workflows) and scenarios 3 and 4 (representing

the AI-integrated workflows) separately first. Scenario 1 (mental health visit) and scenario 2 (UTI visit) were analyzed together to examine patterns in traditional workflow contexts. Likewise, scenario 3 and scenario 4, which involved AI-supported EMR interactions, were compared to identify how decision-making evolved in the presence of AI suggestions.

Following these pairwise comparisons, insights were synthesized across all four scenarios to identify overarching shifts in clinician behavior, information needs, and workflow strategies introduced by AI integration.

This multi-stage analytic process allowed for a nuanced understanding of both scenario-specific behaviors and broader patterns across traditional and AI-enhanced clinical encounters, supporting a comprehensive view of how AI affects primary care workflows.

This chapter outlined the methodological approach undertaken in this research, beginning with a description of the user-centered and contextual design foundations guiding the study, followed by an overview of the participant recruitment process, data collection procedures, and ethical considerations. It also detailed the two complementary analysis methods employed: decision ladder modeling to map clinicians' cognitive workflows and content analysis to extract thematic insights across different clinical scenarios. Together, these methods enabled a comprehensive, mixed-methods exploration of primary care clinicians' decision-making processes in both traditional and AI-enhanced EMR environments.

The findings generated from these analyses are presented and discussed in detail in the following chapter. By combining cognitive modeling and thematic synthesis, the upcoming chapter aims to illuminate key shifts in clinicians' workflows, cognitive strategies, and information needs prompted by AI integration into primary care EMRs.

Chapter 4

Results

This chapter presents the findings of the mixed-methods analysis conducted on semi-structured interview data collected from Ontario-based primary care clinicians, as described in the preceding methodology chapter. Drawing on both decision ladder modeling and qualitative content analysis, the results provide insight into how clinicians interact with traditional and AI-enabled EMR interfaces across different clinical scenarios.

The findings are organized into three main sections. First, a summary of participant demographics is provided to contextualize the sample and ensure transparency in data interpretation. Next, the chapter outlines the cognitive decision-making patterns identified through decision ladder analysis, with a breakdown of results across four scenarios: two representing traditional EMR use and two incorporating AI-supported workflows. This section highlights differences in decision-making approaches between simple cases (e.g., uncomplicated UTI) and more complex presentations (e.g., mental health visits).

The final section presents the results of the qualitative content analysis, which explores emerging themes and recurring patterns in clinician feedback. These thematic findings are further examined through comparative analysis between simple and complex clinical encounters. Attention is given to cognitive work differences, including shifts in information use, workflow strategy, and trust in AI tools, offering a more nuanced understanding of how AI may influence clinical decision-making in primary care.

Together, these results set the stage for the interpretive discussion that follows in Chapter 5.

4.1 Participant Demographics

A total of fourteen primary care clinicians currently practicing in Ontario participated in the study interviews. The sample consisted of ten male-identifying and four female-identifying physicians, with clinical experience ranging from 5 to 37 years (average: 17 years). Participants represented a range of practice models, including eight affiliated with

Family Health Teams (FHTs), two with Family Health Organizations (FHOs), one with a Family Health Network (FHN), two in independent practice, and one associated with a Community Health Centre.

4.2 Decision Ladders

The following section focuses on decision ladders designs based on the four scenarios. Decision ladder models were created based on the predefined coding scheme described in Chapter 3, applied to transcripts from four clinical scenarios.

4.2.1 Scenario 1 – Mental Health Visit (Traditional EMR) Decision Ladder

Figure 4-1 illustrates the decision ladder constructed from clinician interviews responding to a mental health scenario involving a patient presenting with symptoms of severe anxiety. The model captures the cognitive processes and information states clinicians engaged with when using the traditional EMR interface.

Participants consistently began by reviewing the patient's chart, including prior questionnaire scores (e.g., GAD-7), medications, and medical history. This was coded under Activation, Alert, and Observation, followed by identification of key information from the encounter and past records (Information and Identification).

From there, clinicians moved into decision-making processes such as evaluating the System State and Predicting Consequences of different treatment options (e.g., medication vs. counseling). Most interviews reflected use of Evaluate Options and Choice of Task, culminating in specific actions such as documenting notes or prescribing medication (Procedure and Execute).

The following cognitive shortcuts were identified, as visualized in the figure by the corresponding numbers:

- **Shunt (1-a):** Clinicians familiar with the patient sometimes skipped detailed history-taking, relying instead on previously documented context or prior knowledge.

- **Shunt (1-b):** In some cases, clinicians focused on psychological symptoms without explicitly considering potential physical causes such as medication side effects or thyroid issues.
- **Leap (2):** Some participants described prescribing medication based on prior patient response, bypassing the evaluation of alternative treatment options.

These patterns suggest a range of workflow strategies shaped by clinician familiarity with the patient and the routine nature of specific treatment paths in primary care.

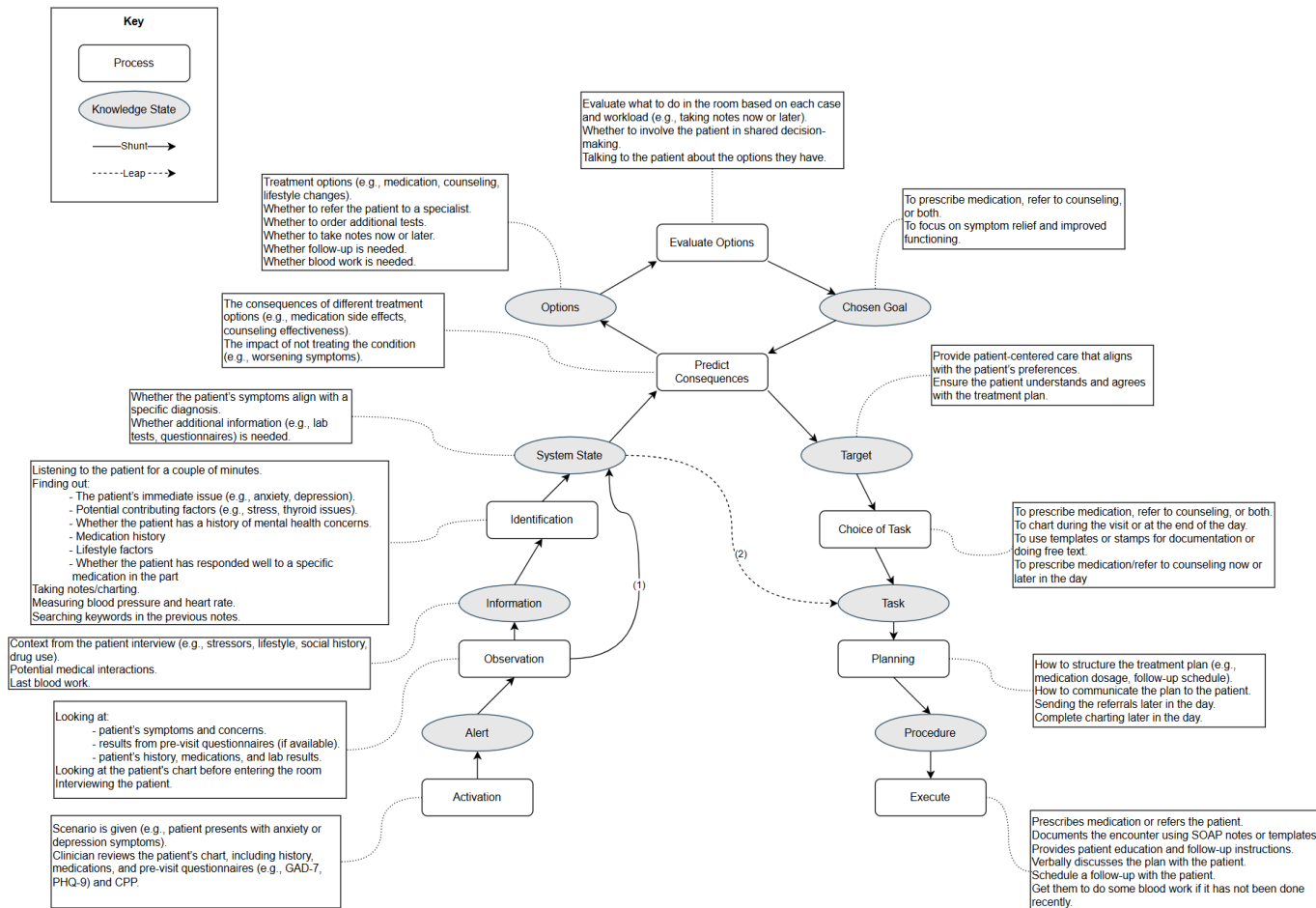


Figure 4-1 Decision Ladder – Scenario 1: Mental Health Visit (Traditional)

4.2.2 Scenario 2 – UTI Visit (Traditional EMR)

Figure 4-2 depicts the decision ladder developed from clinician interviews for a patient presenting with symptoms of an uncomplicated urinary tract infection (UTI), using the traditional EMR interface. This model outlines the cognitive steps and information-gathering behaviors clinicians followed during the encounter.

Clinicians typically initiated the interaction by reviewing the patient's chart and pre-visit test results, such as urine dipstick findings. These steps are reflected in the Activation, Alert, and Observation stages. Clinicians then incorporated contextual information (e.g., symptoms, history of UTIs, sexual health, and allergies) into the Information and Identification stages.

Following this, decision-making proceeded through evaluating the system state and treatment options. This included assessing whether further testing (e.g., urine culture) was needed or whether immediate treatment with first-line antibiotics was appropriate. Actions were ultimately planned and executed based on clinical reasoning and perceived patient risk.

Three distinct cognitive shortcuts were identified in this scenario and are marked in the diagram:

- **Shunt (1):** Some clinicians bypassed interpreting the urine dipstick test altogether due to perceived unreliability (e.g., false negatives), proceeding directly to evaluation or diagnosis based on history and symptoms.
- **Leap (2):** In several cases, clinicians relied solely on pre-visit test results or assumed the UTI was uncomplicated without thoroughly ruling out complicating factors like pregnancy or recurrence. For example, one clinician noted: *“In case the patient doesn't have any complications, no need to visit”*. To clearly illustrate this pattern, the line representing the decision-making pathway for uncomplicated cases in the Decision Ladder has been visually emphasized by increasing its line weight. This adjustment highlights the frequent shortcuts clinicians take in these scenarios.

- **Leap (3):** Similar to Scenario 1, past treatment success influenced decision-making. Clinicians occasionally prescribed the same antibiotic previously used, bypassing broader option evaluation.
- **Leap (4):** Gender-related patterns also emerged in this scenario. Clinicians indicated that decision-making was often more expedited in female patients, as UTIs are more common and their presentations more familiar. In contrast, male patients prompted more in-depth in-room evaluation, with clinicians spending additional time reviewing risks and engaging in patient dialogue.

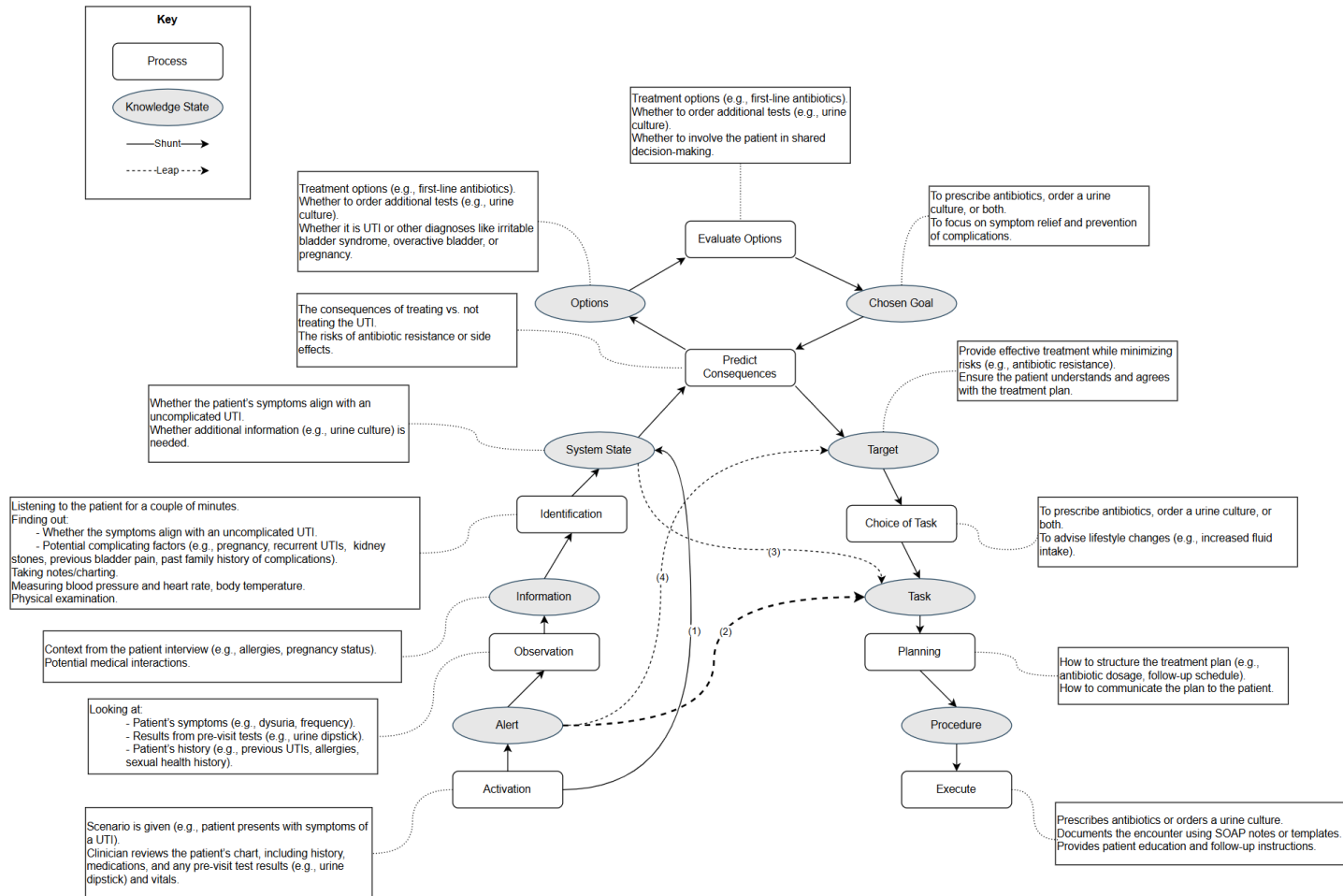


Figure 4-2 Decision Ladder – Scenario 2: UTI Visit (Traditional EMR)

4.2.3 Scenario 3 – Mental Health Visit (AI-Enabled EMR)

Figure 4-3 illustrates the decision ladder constructed from clinician responses to the AI-enabled version of the mental health scenario. The pink-colored text in the decision ladder diagram represents statements and decision points that were unique to the AI-enabled scenario and did not appear in the traditional EMR version. These additions indicate how the presence of AI altered the clinicians' workflow, either by introducing new information elements (e.g., confidence scores, AI-generated summaries) or shifting the nature of tasks (e.g., editing AI-generated notes rather than creating them from scratch).

Clinicians began by reviewing AI-generated content, including patient history summaries, confidence scores, and suggested clinical actions. These observations were coded under Activation, Alert, and Observation, similar to the traditional workflow. However, compared to Scenario 1, there was increased reference to the AI as a source of information, especially during the Information and System State stages. Clinicians described evaluating the validity of AI outputs and comparing them to their own assessments.

The decision-making trajectory continued through Predict Consequences, Options, and Evaluate Options, but a recurring theme in this model was the clinician's active choice to either trust, modify, or override AI suggestions. For example, decisions around whether to accept AI-generated summaries or rephrase them to reflect personal judgment were common, and these steps were reflected in the Task, Planning, and Procedure stages.

The following cognitive shortcuts were identified and are labeled accordingly in the figure:

- **Shunt (1-a):** Clinicians familiar with the patient continued to skip detailed history-taking and relied on prior knowledge, similar to the traditional workflow.
- **Shunt (1-b):** Some clinicians overlooked physical contributors to psychological symptoms, such as thyroid dysfunction or medication interactions.
- **Shunt (1-c):** With AI assistance, some clinicians deferred analytical tasks, such as lab interpretation or confidence scoring, to the system, thereby reducing cognitive

burden. One clinician noted: *“I just ask AI to interpret the lab tests based on the thresholds, it saves me time”*. To underscore the significance of this shift, the corresponding shortcut in the AI-enabled Decision Ladder has been visually emphasized with increased line weight, drawing attention to the offloading of reasoning tasks to the AI system.

- **Leap (2):** Clinicians occasionally prescribed based on previously successful outcomes without exploring alternative treatments, especially if the AI summary aligned with their past choices. This pattern was also observed in the traditional EMR setting, though it appeared less frequently. Accordingly, the line weight for Leap (2) is kept lower in the traditional Decision Ladder and increased in the AI-enabled version to reflect its more prominent role when AI support reinforces existing heuristics.

Compared to the non-AI version of the same scenario, the structure of the decision ladder remains largely consistent, though AI’s role appears to shift certain cognitive efforts, particularly in Information processing and Planning, toward review and validation rather than generation from scratch.

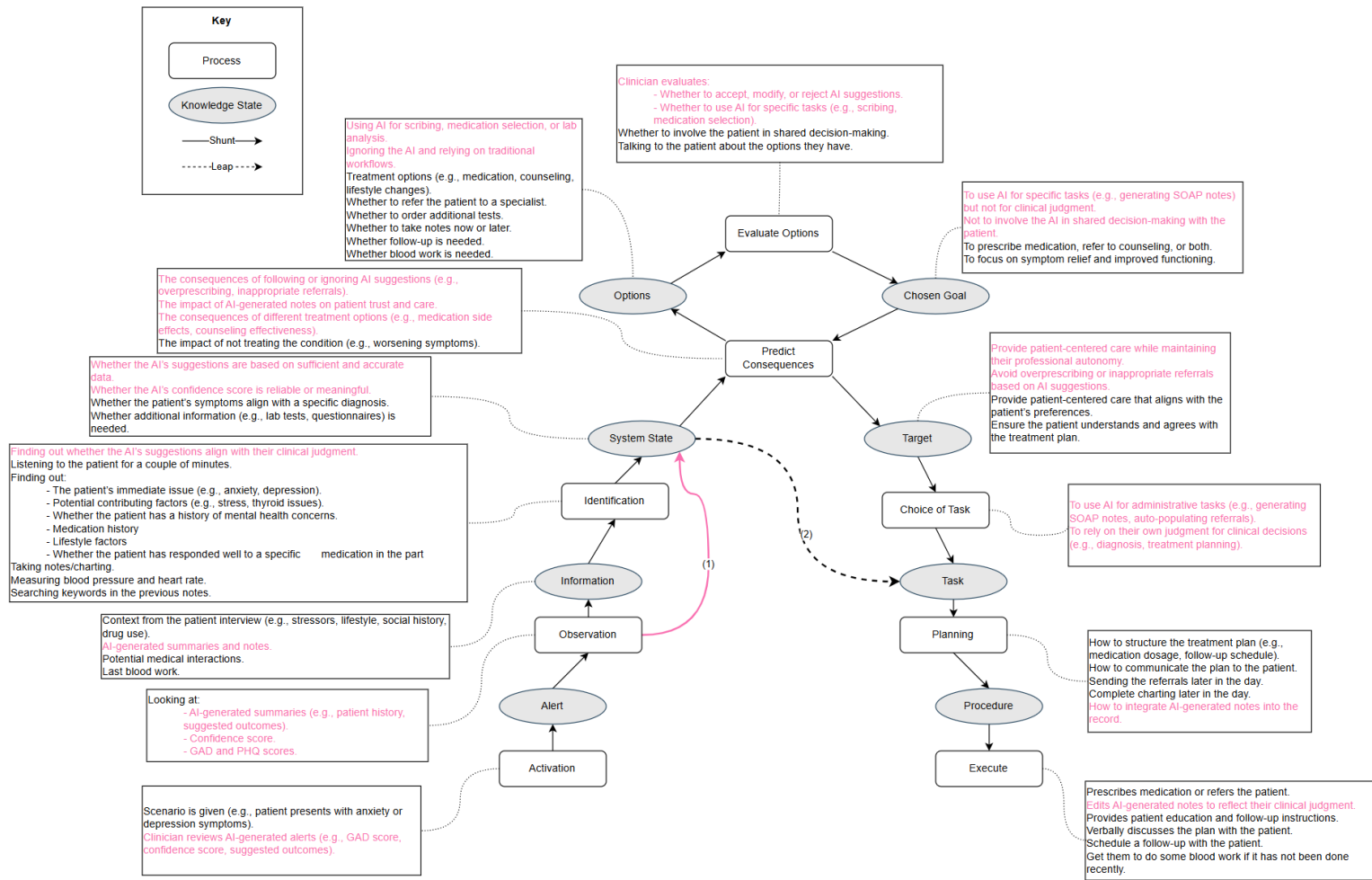


Figure 4-3 Decision Ladder – Scenario 3: Mental Health Visit (AI-Enabled EMR)

4.2.4 Scenario 4 – Urinary Tract Infection (AI-Enabled EMR)

Figure 4-4 presents the decision ladder for a clinician managing an uncomplicated UTI scenario within an AI-enabled EMR interface. As mentioned in the previous section, the pink text in the decision ladder diagram highlights clinician behaviors, decisions, and information-processing steps that were unique to the AI-enabled scenario. These additions reflect how the presence of AI changed the clinical workflow, particularly by introducing automated suggestions, confidence scores, and summaries that could either complement or replace parts of the traditional decision-making process.

Clinicians initiated the workflow by reviewing the AI-generated alerts and patient history summaries. These inputs were coded under Activation, Alert, and Observation. Compared to the traditional version of the scenario, there was increased reference to confidence scores and AI-generated recommendations during the Information and System State stages, where clinicians evaluated whether the AI's suggestions aligned with their clinical expectations.

The decision-making process continued through Evaluate Options, Predict Consequences, and Chosen Goal, with some clinicians explicitly describing a process of deciding whether to accept or reject the AI's recommendation. This extended into Planning and Execution, particularly in how AI-generated notes were used or modified in practice.

Several cognitive shortcuts were observed and labeled in the diagram:

- **Shunt (1):** Some clinicians continued to bypass urine dipstick results due to mistrust in their reliability.
- **Leap (2):** There were instances of relying solely on pre-visit test results or assuming the UTI was uncomplicated without fully assessing for complicating factors. To highlight this shortcut, the line representing the decision-making pathway for uncomplicated cases in the Decision Ladder has been visually emphasized by increasing its line weight. A similar visual emphasis was also applied to the AI-enabled decision-making path to illustrate comparable shortcuts facilitated by AI support.

- **Leap (3):** As with previous scenarios, clinicians sometimes prescribed antibiotics based on prior patient response without evaluating new options.
- **Leap (4):** Gender-related patterns also emerged in this scenario. Clinicians indicated that decision-making was often more expedited in female patients, as UTIs are more common and their presentations more familiar. In contrast, male patients prompted more in-depth in-room evaluation, with clinicians spending additional time reviewing risks and engaging in patient dialogue. This reflects a similar shortcut pattern noted in the traditional Decision Ladder, as previously discussed.
- **Leap (5):** Some clinicians chose to accept the AI's treatment recommendation assuming it was based on sufficient and reliable data, skipping the detailed re-evaluation process. This represents a reinforced cognitive shortcut enabled by AI, distinct from the traditional workflow. To reflect its significance, this new pathway has been visually emphasized in the AI-enabled Decision Ladder with increased line weight and clear separation from standard reasoning paths.
- **Leap (6):** In a few cases, clinicians skipped in-depth patient interviews altogether, relying instead on AI-generated summaries and pre-filled fields.

Notably, Leap (5), marked with a pink dashed arrow, illustrates an AI-specific cognitive shortcut: the assumption that AI-generated recommendations were sufficiently accurate and reliable to proceed without independent verification. This leap reflects a shift in clinician behavior where the AI system was treated as a trusted intermediary in the diagnostic or planning process, bypassing otherwise standard verification or re-evaluation stages. To visually highlight the prominence of this shortcut, the corresponding path in the Decision Ladder has been emphasized with increased line weight.

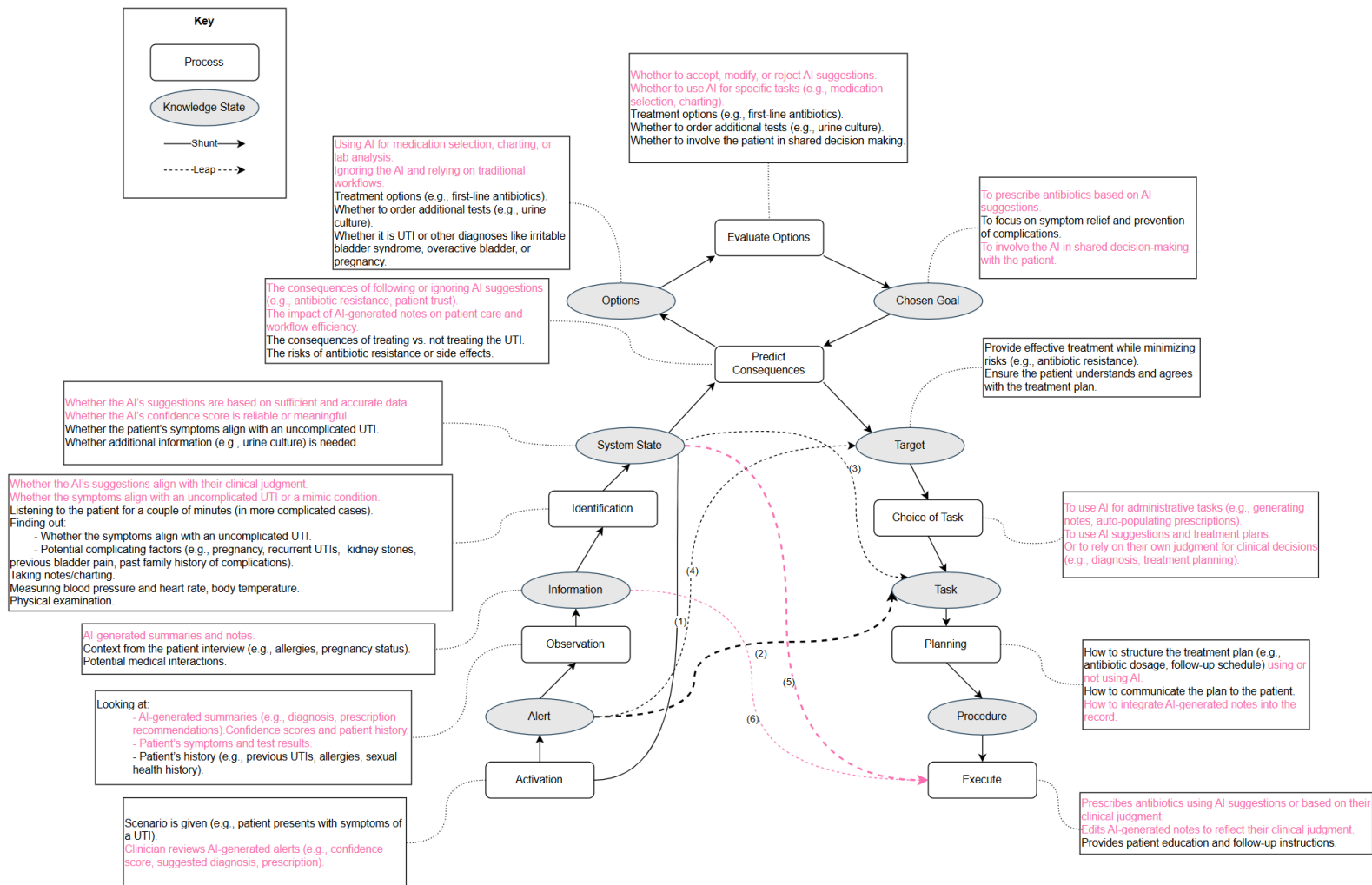


Figure 4-4 Decision Ladder – Scenario 4: UTI Visit (AI-Enabled EMR)

4.3 Exploratory Frequency of Shortcuts Across Scenarios

While the DL analysis maps the possible pathways available to clinicians, the coded interview data also provided insight into the *relative frequency* with which certain shortcuts were reported. As also mentioned in the methodology section, Table 4-1 summarizes the approximate frequency of shortcut use across the four modeled scenarios.

Table 4-1 Approximate Frequency of Shortcuts Observed in Interview Data

Scenario	Shortcut (Shunt/Leap)	Frequency	Illustrative Context
Mental Health – Traditional EMR	Shunt (1-a)	5	Clinicians familiar with the patient sometimes skipped detailed history-taking, relying instead on previously documented context or prior knowledge.
	Shunt (1-b)	4	In some cases, clinicians focused primarily on psychological symptoms without explicitly considering potential physical causes (e.g., medication side effects, thyroid issues).
	Leap (2)	4	Some participants described prescribing medication based on prior patient response, bypassing evaluation of alternative treatment options.
UTI – Traditional EMR	Shunt (1)	4	Some clinicians bypassed interpreting the urine dipstick test altogether due to perceived unreliability (e.g., false negatives), proceeding directly to

			evaluation or diagnosis based on history and symptoms.
	Leap (2)	6	In several cases, clinicians relied solely on pre-visit test results or assumed the UTI was uncomplicated without thoroughly ruling out complicating factors (e.g., pregnancy, recurrence).
	Leap (3)	5	Past treatment success influenced decision-making, where clinicians occasionally prescribed the same antibiotic previously used, bypassing broader option evaluation.
	Leap (4)	3	Gender-related patterns emerged in this scenario. Clinicians indicated that decision-making was often more expedited in female patients (due to the higher prevalence and familiarity of presentation). In contrast, male patients prompted more detailed evaluation, with clinicians spending additional time reviewing risks and engaging in patient dialogue.
Mental Health – AI-Enabled EMR	Shunt (1-a)	4	Clinicians familiar with the patient continued to skip detailed history-taking and relied on prior knowledge, mirroring the traditional workflow.
	Shunt (1-b)	3	Some clinicians overlooked possible physical contributors to psychological

			symptoms (e.g., thyroid dysfunction, medication interactions), focusing instead on presenting psychological cues.
	Shunt (1-c)	6	With AI assistance, some clinicians deferred analytical tasks—such as lab interpretation or confidence scoring—to the system, thereby reducing cognitive burden. One clinician remarked: <i>“I just ask AI to interpret the lab tests based on the thresholds—it saves me time.”</i>
	Leap (2)	6	Clinicians occasionally prescribed based on previously successful outcomes without exploring alternative treatments, particularly when the AI summary supported their past decisions. This shortcut was also noted in the traditional EMR scenario, though it appeared less frequently.
UTI – AI-Enabled EMR	Shunt (1)	4	Some clinicians continued to bypass urine dipstick results due to mistrust in their reliability.
	Leap (2)	6	Clinicians occasionally relied solely on pre-visit test results or assumed the UTI was uncomplicated without fully assessing for complicating factors.
	Leap (3)	5	As with previous scenarios, clinicians sometimes prescribed antibiotics based on

			prior patient response without evaluating new options.
	Leap (4)	4	Gender-related patterns again emerged. Decisions were expedited for female patients, as UTIs are more common and presentations more familiar, whereas male patients prompted more in-depth risk assessment and dialogue.
	Leap (5)	7	Some clinicians chose to accept the AI's treatment recommendation, assuming it was based on sufficient and reliable data, thereby skipping detailed re-evaluation. This represents a reinforced cognitive shortcut uniquely enabled by AI.
	Leap (6)	3	In a few cases, clinicians skipped in-depth patient interviews altogether, relying instead on AI-generated summaries and pre-filled fields. This illustrates the growing delegation of clinical reasoning tasks to AI in routine care.

Across the four scenarios, analysis of shortcut frequencies (shunts and leaps) revealed consistent patterns in how clinicians adapted their reasoning processes to case type (routine vs. complex) and system context (traditional EMR vs. AI-enabled EMR). The frequency estimates suggest that shortcuts were common and context-dependent. For example, in UTI visits, clinicians more frequently skipped deliberative steps due to the routine nature of the condition and reliance on either lab results or AI prompts. In contrast, mental health visits

displayed more variability, with shortcuts more closely tied to clinician experience and trust in AI-generated notes.

It is important to emphasize that these counts are approximations derived from qualitative narratives rather than structured observation. Not all shortcuts were explicitly mentioned, and some were inferred from clinician descriptions of “typical practice.” This demonstrates the *potential value* of systematically measuring shortcut frequency but cannot be interpreted as quantitative evidence.

4.4 Content Analysis

The following section analyzes the content based on four scenarios. This analysis is divided into two main parts: one comparing scenario 1 and scenario 2, and the other comparing scenario 3 and scenario 4.

4.4.1 Content Analysis for Scenarios 1 & 2

The content analysis of clinician interviews regarding Scenarios 1 (Mental Health) and 2 (UTI) revealed distinct patterns, primarily associated with information processing. Given that these scenarios involved traditional EMRs without advanced decision-support capabilities, the patterns addressed documentation practices, clinician-patient interactions, historical information referencing, and clinical decision-making routines.

Below are thematic subcategories accompanied by brief explanatory texts, representative participant quotes, and summarized clearly in Table 4-2 and Table 4-3.

Table 4-2 Themes Identified in Mental Health Scenario (Scenario 1)

Category	Sub-Category	Description	Participant Quotes
Information Processing	Detailed Patient History Review	Clinicians conduct thorough reviews of mental health histories due to complexity and individualized nature of visits.	<i>“How often she's visited before... I probably have a look at the questionnaire too.”</i> – Participant 1
			<i>“Especially for mental health, it's a whole different ball game.”</i> – Participant 8
			<i>“...If they're super complex in which case I'm like, all right, we gotta look at your thyroids. We gotta look at your medications. you've had 15 drugs in the past which ones worked which that's what I'm playing their chart”</i> – Participant 8
	Direct Patient Interaction	Visits emphasize direct interaction, focusing less on screens or checklists and more on patient narratives.	<i>“Sometimes I wouldn't even do the GADs... I would see them and just start taking a history.”</i> – Participant 4
		Detailed and subjective note-taking occurs due to	<i>“I'd probably start jotting down a few notes just so I</i>

Category	Sub-Category	Description	Participant Quotes
	Detailed Note-Taking	complexity, variability, and the depth of patient narratives in mental health cases.	<i>don't forget everything that she said.</i> – Participant 1
			<i>“Lots of details differ from one patient to the next.”</i> – Participant 7
	Historical Information Utilization	Clinicians refer extensively to historical patient data, including prior mental health treatments, referrals, and notes.	<i>“Pulling up specific notes, but depends on complexity and thickness of the chart.”</i> – Participant 14
	Holistic Consideration and Referrals	Clinicians take multiple factors into account, including referrals and therapeutic resources, to support patient care comprehensively.	(No direct quote provided; inferred from descriptions)

- **Detailed Patient History Review**

Clinicians conducted comprehensive reviews of patient histories due to the inherently complex and individualized nature of mental health visits. This thoroughness included examining patient questionnaires and previous visitation data closely to inform their clinical assessments.

- **Direct Patient Interaction**

Mental health consultations emphasized extensive patient interaction, often placing less emphasis on structured assessments or checklists and more on organic, conversational engagement to elicit patient narratives.

- **Detailed Note-Taking**

Documentation practices in mental health encounters were detailed and subjective, reflecting the nuanced and individualized narratives patients provided. Clinicians documented notes extensively during or shortly after patient interactions to capture significant details.

- **Historical Information Utilization**

Clinicians frequently utilized historical patient data, including prior treatment notes, referrals, and the complexity of historical documentation, to enhance their understanding and support clinical decision-making comprehensively.

- **Holistic Consideration and Referrals**

Clinicians considered broader, holistic factors during mental health visits, incorporating additional resources such as referrals, therapeutic recommendations, and multidisciplinary support into patient care, reflecting the complexity of managing mental health conditions.

Table 4-3 Themes Identified in UTI Scenario (Scenario 2)

Category	Sub-Category	Description	Participant Quotes
Information Processing	Short and Algorithmic Visits	Visits are brief, often algorithmic, with minimal direct clinician-patient interaction, typically handled by nurses unless complications arise.	<p><i>“Often these appointments are less than 5 minutes... in some cases I don't even see the patient.”</i> – Participant 1</p> <p><i>“Often these kinds of visits I would just type very little and do have and make it a very short appointment.”</i> – Participant 1</p>
	Skipping Diagnostic Tests	Clinicians often skip the urine dip test, relying on empirical treatment due to perceived test inaccuracies.	<p><i>“You can treat her empirically... the test is very inaccurate in any case.”</i> – Participant 1</p> <p><i>“So wherever that is in the in the setup here would look at that and then you know if you like that result was and then, umm, you know in this case you don't even actually need that test”</i> – Participant 10</p>
	Variability in Detail of Documentation	Documentation is brief and standardized, expanding only in	<i>“Momentary documentation for a simple UTI, as opposed to anxiety... lots of details</i>

Category	Sub-Category	Description	Participant Quotes
		cases of complexity or unusual presentations.	<i>differ from one patient to the next.</i> – Participant 7
	Complexity-driven Investigations	More extensive investigations are triggered by complications, atypical presentations (e.g., male patients), or when standard protocols might not suffice.	<i>“This is a male getting a UTI, automatically complex... any past history of kidney or bladder issues?”</i> – Participant 8
<i>“Sometimes we need to see the patient. As the patient has some complications, maybe she's diabetic or she has other comorbidities and occasional. Examine the patient and so on, and make sure they're okay.”</i> – Participant 1			
<i>“Some of them have, like, you know, overactive bladder. Like does she have like pyelonephritis? Like a more serious infection, you know, could this person be pregnant? Which case with that modify mean she's 48? So be looking in the history to see does she have that?”</i>			

Category	Sub-Category	Description	Participant Quotes
			<i>Has she actually been on medication for that?” – Participant 10</i>
	Utilization of Previous Treatments	Clinicians frequently refer back to previous treatment effectiveness, medication histories, and past lab results when available.	<i>“I might look in old scripts, see last treatment... was it effective again?” – Participant 14</i>

- **Short and Algorithmic Visits**

UTI visits were characteristically brief, standardized, and algorithmic, typically involving minimal clinician-patient direct interaction. Clinical tasks were often delegated to nurses, except in complicated cases, resulting in rapid patient throughput.

- **Skipping Diagnostic Tests**

Clinicians commonly skipped diagnostic tests like the urine dip test, considering these tests unreliable. Instead, empirical treatments based on patient history or symptom presentations were prioritized.

- **Variability in Detail of Documentation**

Documentation during UTI visits was generally brief and standardized. Detailed documentation was typically only undertaken in complex or atypical cases, contrasting with the comprehensive documentation approach in mental health scenarios.

- **Complexity-driven Investigations**

Clinicians undertook additional investigative efforts primarily when encountering atypical or complex presentations, such as UTIs in male patients, who typically necessitate more extensive investigation and differential considerations.

- **Utilization of Previous Treatments**

Historical treatment efficacy and past medication responses were critical elements considered by clinicians during UTI visits. Reviewing previous treatments allowed clinicians to swiftly guide decision-making and determine appropriate clinical actions.

4.4.2 Content Analysis for Scenarios 3 & 4

Analysis of clinician interviews concerning the AI-integrated EMR scenarios (Scenarios 3 & 4) revealed themes highlighting clinicians' perceptions, trust, reliance on AI, and its impact on their cognitive, emotional, and practical workflows. Themes were separately categorized for Mental Health Scenario (Scenario 3), UTI Scenario (Scenario 4), and General Themes relevant across both scenarios.

Below are thematic subcategories accompanied by brief explanatory texts, representative participant quotes, and summarized clearly in Table 4-4, Table 4-5, and Table 4-6.

Table 4-4 Themes Identified in Mental Health Scenario (Scenario 3)

Category	Sub-Category	Description	Participant Quotes
Trust and Reliance on AI	Skepticism about AI Accuracy	Clinicians doubt AI accuracy and sometimes disregard results as superficial or premature, limiting reliance on AI suggestions.	<i>“Skipping looking at the test result because it’s inaccurate.”</i> – Participant 1
			<i>“I think, uh, I think that might just throw people off a little bit..., cause mental health services is pretty broad. People just may misunderstand what that what that actually means.”</i> – Participant 12
	Oversimplification of Mental Health Problems	Clinicians perceive AI-generated mental health assessments as oversimplified, lacking essential patient context and narrative.	<i>“Massive oversimplification of mental health problems.”</i> – Participant 1
			<i>“I feel like I probably need to have more context and more discussion. And so it feels like this is jumping the gun a little bit to me in terms of like the suggested outcome”</i> – Participant 14

Category	Sub-Category	Description	Participant Quotes
			<p data-bbox="1076 338 1416 590"><i>“there's just that jump right to you know, prescribe select medication” – Participant 3</i></p> <p data-bbox="1076 632 1409 884"><i>“And I still have to go and talk to the patient for like 20 or 30 minutes to figure out why they're anxious.” – Participant 1</i></p> <p data-bbox="1076 926 1422 1556"><i>“There's really strong evidence for other things that we need to consider, you know, weight bearing exercise, cardiovascular exercise, again, consistent hydration with water, dietary selection like this stuff there, there, there are sort of bodies of evidence out there ...” – Participant 3</i></p> <p data-bbox="1076 1598 1414 1797"><i>“History is a bit thin. The guide indicates severe anxiety, but there's no contextualization with</i></p>

Category	Sub-Category	Description	Participant Quotes
			<p><i>their past mental health history.... It needs to be a little bit more intelligent”</i> – Participant 4</p>
			<p><i>“You know, in this particular case, like a GAD score is interesting, but it in itself is not diagnostic right.”</i> – Participant 10</p>
			<p><i>“...you can't dip your toe in the in the pond, tell the doc what to consider clinically without being comprehensive about it”</i> – Participant 3</p>
	<p>Legal and Ethical Concerns</p>	<p>Clinicians express anxiety over potential legal consequences of declining AI-generated recommendations, particularly in sensitive mental health cases.</p>	<p><i>“What if AI suggested something, I declined it, and turned out wrong?”</i> – Participant 7</p> <p><i>“I needed my own defense to say why, and there can be some preloaded responses and there needs to be free text if I'm gonna record that. I disagreed</i></p>

Category	Sub-Category	Description	Participant Quotes
			<p><i>with an AI. I'm gonna be really nervous about that.</i>” – Participant 7</p> <p><i>“My fear of this automatically being put into the chart is what is being documented as to what I did it did not do. How can this be used against me medical legally.”</i> – Participant 8</p> <p><i>“Let's go to the worst case scenario. Somebody commit suicide from their anxiety family decides to sue me. They get an audit of my EMR and they say your AI told you to refer and you deleted that line your AI set to start a medication you delete that line. Why'd you do such a thing?”</i> – Participant 8</p>
		Concerns that reliance on numerical AI	<i>“I mean, I think I think it would make me look like</i>

Category	Sub-Category	Description	Participant Quotes
Cognitive and Emotional Impact	Clinical Autonomy and Proficiency	assessments could make clinicians appear less professional and skilled.	<i>I'm at some kind of low level technician or something, that didn't really understand what I was doing</i> – Participant 1
			<i>“it might not be that good, because maybe that's gonna lead you to do more tasks or like, you know, like just be always kind of like lacking confidence in your own clinical acumen, right?”</i> – Participant 10
			<i>“I'm going to want to spend quite a bit of time explaining why I think I'm smarter than the AI.”</i> – Participant 7
Human-Centered Care	Importance of Human Connection	AI's limitations in human interaction are highlighted; clinicians emphasize essential	<i>“I don't know that you necessarily make people feel better. ... would people feel cared for? Probably not. Would they feel confident in what you</i>

Category	Sub-Category	Description	Participant Quotes
		human-to-human interaction.	<p><i>said? Probably not. And would they seek out a second opinion from a human they could converse with?, probably.” – Participant 4</i></p> <p><i>“I probably wouldn't say that the AI recommended this because it gets away from the whole interaction and makes the patient feel like why didn't I just talk to an AI it's the point of booking important with you for me be very much.” – Participant 8</i></p>
	Shared Decision-Making	AI integration should enhance, not replace, human involvement in shared decision-making.	<p><i>“I wouldn't say AI recommended this; it undermines interaction.” – Participant 8</i></p>
Workflow and Practical Considerations	Fear of Delayed Response	AI could lead to delayed clinical actions due to processing	<p><i>“Patient completes questionnaire at midnight Friday, I won't see it until Monday. you know, I do</i></p>

Category	Sub-Category	Description	Participant Quotes
		questionnaires prior to clinical encounters.	<i>look at it on a Saturday and then I'm like, well, I logged in to look at this, and now I have information saying that they're at risk of harming themselves would have no context about it. Which can put you in a bit of a tricky situation” – Participant 12</i>
	AI as a Second Set of Eyes	Clinicians appreciated AI's role as a complementary support system, acting as an additional check or "second set of eyes." Particularly in complex mental health scenarios.	<p><i>“I would love AI to maybe sometimes give me a differential or some other suggestion that maybe I forgot or didn't think about.” – Participant 9</i></p> <p><i>“You know that the AI is putting together information that might not be obvious to me before the AI was doing this, I'm might not be the best example because in this case it's all really obvious.” – Participant 7</i></p>

Category	Sub-Category	Description	Participant Quotes
			<p><i>“maybe it suggests a medications that you know I wasn't thinking of or like if you click send referral maybe it has like a list of some places that I hadn't thought about for sending a referral.”</i> – Participant 10</p>

- **Trust and Reliance on AI**

- **Skepticism about AI Accuracy:** Clinicians frequently doubted AI-generated assessments and recommendations in mental health scenarios, often perceiving them as superficial or inaccurate, and therefore disregarded them in favor of their clinical judgment.
- **Oversimplification of Mental Health Problems:** There was strong concern that AI's approach oversimplified complex mental health conditions, neglecting the depth and personalized context critical for accurate diagnosis and treatment planning.
- **Legal and Ethical Concerns:** Clinicians expressed significant anxiety over potential legal and ethical implications when declining AI recommendations in mental health scenarios, highlighting the perceived risks of relying heavily on AI in sensitive situations.

- **Cognitive and Emotional Impact**

- **Clinical Autonomy and Proficiency:** There was concern among clinicians that reliance on AI-driven numerical assessments could undermine their professional image and perceived clinical autonomy, potentially reducing patient confidence in clinician expertise.
- **Human-Centered Care**
 - **Importance of Human Connection:** Clinicians emphasized maintaining strong human connections during mental health interactions, highlighting AI's limitations in capturing the nuanced, empathetic nature of mental health care.
 - **Shared Decision-Making:** Clinicians supported the use of AI as a tool to enhance shared decision-making with patients, provided it complements rather than replaces personalized clinician-patient interactions.
- **Workflow and Practical Considerations**
 - **Fear of Delayed Response:** Concerns were raised regarding potential delays in addressing urgent patient needs, particularly when patient questionnaires processed by AI were completed well ahead of clinician review, potentially missing timely interventions.
 - **AI as a Second Set of Eyes:** Clinicians appreciated AI's role as a complementary support system, acting as an additional check or "second set of eyes." Particularly in complex mental health scenarios, clinicians valued AI's potential to suggest considerations they might overlook, such as differential diagnoses or treatment alternatives, ultimately leaving the final clinical decisions in their hands.

Table 4-5 Themes Identified in UTI Scenario (Scenario 4)

Category	Sub-Category	Description	Participant Quotes
Trust and Reliance on AI	Trust in AI Recommendations	Clinicians are more willing to rely on AI suggestions for straightforward UTI management, given limited treatment variability.	<i>“Nice, there aren't that many medications for this anyway.”</i> – Participant 13
			<i>“I think I would be OK with the AI selecting medication, especially if it kinda looked through all their medications and pick something that didn't interact like had that kind of cross check because ultimately I would always be kind of double checking it anyways.”</i> – Participant 6
	Acceptance of AI for Medication Suggestions	AI is welcomed for medication suggestions due to the simplicity and limited options available for UTIs.	<i>“If it auto-populated a medication, I would love that.”</i> – Participant 13 <i>“If you say prescribe select medication that's even helpful to me that will save me time if I can just collect click that button and then a number of choices come up”</i> – Participant 9

Category	Sub-Category	Description	Participant Quotes
	Differential Reliance (Simple Cases)	Clinicians rely more on their memory and clinical judgment rather than AI prompts for simple, routine cases.	<i>“Doesn't take much note since it's easy to remember.”</i> – Participant 1
AI as a Decision Support Tool	Guideline Support and Charting	Clinicians appreciate AI summarizing guidelines, flagging abnormalities, and streamlining documentation and charting.	<i>“...and I want to know what the latest guidelines are..”</i> – Participant 7
			<i>“Preferably maybe linked to guidelines like around treatment for uncomplicated UTI”</i> – Participant 10
			<i>“Obviously there would be a pathway like are they pregnant?... I mean obviously with the medication too, I don't know how your algorithm if it's like if it's like sort of smart and can take into consideration what medications they're on and allergies or if it's just like generally speaking like a float sheet.”</i> – Participant 13
			<i>“...AI can be aware of those guidelines and can apply them</i>

Category	Sub-Category	Description	Participant Quotes
			<i>to this particular patient once it recognizes what the situation with the patient is” – Participant 7</i>
	Treatment and Medication Management	AI's ability to suggest evidence-based medications and cross-check interactions highly valued.	<i>“I'd be okay with AI selecting medication and checking interactions.” – Participant 6</i>

- **Trust and Reliance on AI**

- **Trust in AI Recommendations:** Clinicians exhibited greater openness and trust in AI recommendations for straightforward conditions like UTIs, as the clinical pathways and treatments involved were more predictable and limited in scope.
- **Acceptance of AI for Medication Suggestions:** AI-generated medication suggestions were well-received, particularly due to the limited variability and straightforward nature of UTI treatment, making AI recommendations highly practical and efficient.
- **Differential Reliance (Simple Cases):** In uncomplicated cases, clinicians often relied on their own clinical knowledge and memory rather than actively referencing AI prompts, indicating selective reliance based on clinical complexity.

- **AI as a Decision Support Tool**

- **Guideline Support and Charting:** AI was valued for effectively summarizing clinical guidelines, identifying abnormal findings, and simplifying documentation processes, thereby streamlining workflow.
- **Treatment and Medication Management:** AI's ability to suggest evidence-based medications and systematically check for drug interactions was considered particularly beneficial, enhancing the safety and efficacy of medication prescriptions.

Table 4-6 General Themes relevant across Scenarios 3 & 4

Category	Sub-Category	Description	Participant Quotes
Trust and Reliance on AI	AI as a Complementary Tool	Clinicians prefer AI recommendations to support, not drive, clinical decisions, serving as a “second set of eyes”.	<i>“AI might give suggestions I didn't think about.” – Participant 9</i>
			<i>“So when the AI can help me with the hard decisions that aren't intuitive, that would be fantastic, right?” – Participant 7</i>

Category	Sub-Category	Description	Participant Quotes
			<p><i>“If it auto populated a suggestion, I would love that because there are only a handful” – Participant 13</i></p>
			<p><i>“I feel like they could almost help you with some charting with the physical exam aspect like put that in for you to fill out.” – Participant 6</i></p>
	<p>Risks of AI-induced Bias</p>	<p>AI suggestions may introduce biases, potentially influencing clinicians prematurely before independent evaluation.</p>	<p><i>“Someone is biasing me already to refer this patient...you're really not thinking because you there's already an outcome in front of you and you if the clinician doesn't arrive in an outcome themselves, then they already getting biased before they even start thinking about the case” – Participant 1</i></p>

Category	Sub-Category	Description	Participant Quotes
	Oversimplification and Lack of Nuance	AI perceived as oversimplifying cases or missing detailed patient contexts, potentially reducing accuracy and clinical relevance.	<i>“History is thin, there's no contextualization.” – Participant 4</i>
			<i>“I'm trying to think of something kind of vague or undifferentiated, like dizziness. I don't know what kind of questionnaire you would be able to give AI for something like that.” – Participant 6</i>
			<i>“So suggested outcome like in a primary care visit. That means nothing to me, you know, from an IT perspective, that may mean something to you, but from my perspective, it doesn't mean anything.” – Participant 5</i>
	Confidence Scores	Clinicians request confidence scores for AI recommendations,	<i>“To me that confidence score I think can be calibrated or used for a</i>

Category	Sub-Category	Description	Participant Quotes
		especially in complex or sensitive cases.	<i>certain types of suggestions, but you'd have to use it very selectively.” – Participant 14</i>
AI as a Decision Support Tool	Explanations and Reasoning	AI systems that explain recommendations clearly are highly preferred by clinicians, enhancing trust and usability.	(No direct quote provided; inferred from descriptions)
	Pattern Recognition and Template Utilization	AI supports clinical decision-making by identifying patterns in patient data and providing structured, simplified templates and easy-access links for common clinical actions like referrals, enhancing clinician efficiency and decision accuracy.	<p><i>“And so I think there is definitely value to using AI on an individual chart basis to look for patterns and come to conclusions and give suggestions that are decision support.” – Participant 7</i></p> <p><i>“I think the power of the AI is in the in having some templates that are not too complex and mostly having those</i></p>

Category	Sub-Category	Description	Participant Quotes
			<i>links like that easy referral that's really handy” – Participant 13</i>
Cognitive and Emotional Impact	Cognitive Workload and Efficiency	AI can streamline workflow and reduce cognitive load but may occasionally add complexity or cognitive overhead.	<i>“No doubt it will cause increased cognitive load.” – Participant 10</i>
			<i>“I'm more interested in not being overburdened with additional work more than I'm interested in training the AI to get better.” – Participant 7</i>
	Emotional Responses and Frustrations	Clinicians express frustrations regarding AI limitations and insufficient practical support in their workflows.	<i>“It didn't decrease my administrative burden... and so you know, value added here is not as much as I would hope it to be” – Participant 2</i>
<i>“Here is no extraneous clicking, but that's not valuable” – Participant 5</i>			
<i>“It might not be that good, because maybe that's gonna lead you to</i>			

Category	Sub-Category	Description	Participant Quotes
			<p><i>do more tasks or like, you know, like just be always kind of like lacking confidence in your own clinical acumen, right?” – Participant 10</i></p>
			<p><i>“I could take half the visit to explain it to them or I could show them a multi page document that they won't read anyway that I probably don't understand and neither do they.” – Participant 7</i></p>
			<p><i>“Most likely I'm not really getting any significant help from this and frankly it's taking up more of my time.” – Participant 7</i></p>
			<p><i>“I wouldn't really go out of my way to tell patients I was using it... it doesn't really matter. I think</i></p>

Category	Sub-Category	Description	Participant Quotes
			<i>people just want the service.” – Participant 4</i>
Human-Centered Care	Patient Awareness of AI Integration	Most clinicians are reluctant to discuss AI integration explicitly with patients, perceiving it as potentially disruptive or unnecessary.	<i>“I don't think it would help them, and I don't see how they can be harmed if I don't [let them know].” – Participant 7</i>
			<i>“I probably wouldn't say that the AI recommended this because it gets away from the whole interaction and makes the patient feel like why I didn't just talk to an AI” – Participant 8</i>
			<i>“If it was a requirement that I have to tell every patient that I see that I'm using an EMR that has AI built-in, that would be a barrier... I wouldn't wanna do that” – Participant 12</i>

Category	Sub-Category	Description	Participant Quotes
			<p data-bbox="1094 338 1382 653"><i>“I don't feel an obligation to say to a patient all the details about the decision support tools that I'm using” – Participant 7</i></p> <p data-bbox="1094 684 1409 940"><i>“Clinicians can turn their brain off quickly because someone else is thinking for them.” – Participant 1</i></p>
<p data-bbox="250 1339 456 1430">Risk of Over-Reliance on AI</p>	<p data-bbox="488 1339 699 1430">Loss of Clinical Creativity</p>	<p data-bbox="766 1230 1073 1539">Clinicians fear systematic AI suggestions could limit their clinical creativity, judgment, and critical thinking skills.</p>	<p data-bbox="1094 978 1406 1287"><i>“You're being mindless, you know, and mindlessness needs leads to all kinds of harms to patients” – Participant 1</i></p> <p data-bbox="1094 1318 1419 1797"><i>“There's already an outcome in front of you and you if the clinician doesn't arrive in an outcome themselves, then they already getting biased before they even start thinking about the case” – Participant 1</i></p>

Category	Sub-Category	Description	Participant Quotes
			<i>“Helpful for charting physical exam aspects.”</i> – Participant 6
Workflow and Practical Considerations	Time Efficiency and Documentation	AI perceived as helpful for improving clinical efficiency, particularly in standard tasks like documentation and prescription writing.	<i>“I’m not fearful; you can always argue against AI based on clinical judgment.”</i> – Participant 9
	Legal and Ethical Comfort (Low-risk Scenarios)	Some clinicians feel less legally and ethically concerned about using AI	<i>“I don’t care because I view AI as a partner, not a replacement but other people wouldn’t.”</i> – Participant 7

- **Trust and Reliance on AI**

- **AI as a Complementary Tool:** Across scenarios, clinicians consistently preferred AI to function as an advisory or secondary source of recommendations, supporting rather than driving clinical decisions independently.
- **Risks of AI-induced Bias:** Concerns were expressed regarding AI potentially biasing clinical judgment by presenting predefined recommendations prematurely, possibly affecting independent clinical assessments.

- **Oversimplification and Lack of Nuance:** Clinicians recognized that AI might oversimplify patient contexts or fail to capture nuanced clinical details essential for accurate diagnosis and management, particularly in complex cases.
- **Confidence Scores:** Clinicians frequently requested AI confidence scores as a means of evaluating the reliability and trustworthiness of recommendations, especially in clinically complex or sensitive scenarios.
- **AI as a Decision Support Tool**
 - **Explanations and Reasoning:** Clinicians favored AI systems that clearly explained the rationale behind recommendations, improving clinicians' confidence in applying AI-supported decisions in practice.
 - **Pattern Recognition and Template Utilization:** Clinicians recognized significant value in AI's ability to identify patterns within individual patient charts, helping highlight potential issues and inform clinical judgments. Additionally, they emphasized the practical utility of AI-generated templates, which simplify documentation and provide accessible, structured links to common clinical actions such as referrals.
- **Cognitive and Emotional Impact**
 - **Cognitive Workload and Efficiency:** AI was perceived as beneficial in reducing cognitive workload through streamlined information processing. However, it also occasionally introduced additional cognitive complexity through the need to interpret and validate AI outputs.
 - **Emotional Responses and Frustrations:** Clinicians expressed varying levels of frustration with AI limitations, especially when AI failed to alleviate administrative burdens or provide tangible improvements in clinical workflows.
- **Human-Centered Care**

- **Patient Awareness of AI Integration:** Most clinicians preferred not to explicitly disclose AI integration to patients, viewing it as potentially disruptive or unnecessary, especially when they perceived it as having little impact on patient interactions.
- **Risk of Over-Reliance on AI**
 - **Loss of Clinical Creativity:** Clinicians were wary of the potential reduction in clinical creativity and critical thinking due to reliance on standardized AI-generated suggestions, advocating for maintaining clinical judgment flexibility.
- **Workflow and Practical Considerations**
 - **Time Efficiency and Documentation:** AI's ability to automate routine clinical tasks, such as charting and prescription management, was generally perceived as positively contributing to workflow efficiency and reducing documentation burdens.
 - **Legal and Ethical Comfort (Low-risk Scenarios):** Clinicians reported fewer legal and ethical concerns regarding AI usage in simpler, lower-risk clinical situations, such as UTIs, viewing AI as less controversial and more easily defensible in these contexts.

This chapter presented comprehensive results from the thematic content analysis, including detailed thematic insights and structured decision ladders, which visually illustrated clinician workflows and decision-making processes across traditional and AI-integrated EMR scenarios. Findings captured clinicians' perceptions, cognitive and emotional responses, trust dynamics, patient interaction patterns, and practical workflow considerations. The decision ladders provided additional clarity by mapping explicit cognitive steps and decision points encountered by clinicians in each scenario. These results lay the groundwork for a deeper exploration and critical analysis of their implications, which will be elaborated upon in the following discussion chapter (Chapter 5).

Chapter 5

Discussion

This chapter presents an in-depth discussion and synthesis of the study's findings, drawing from both the thematic content analysis and decision ladder models developed across four clinical scenarios. Through these complementary lenses, the chapter explores how the integration of AI into EMR systems reshapes clinical workflows, decision-making strategies, and cognitive processes in primary care. Particular emphasis is placed on interpreting the observed differences between traditional and AI-supported environments, as well as between mental health and UTI-related scenarios. By comparing and integrating insights across all scenarios, this chapter aims to build a holistic understanding of clinician-AI interaction, inform user-centered EMR design, and provide evidence-based recommendations for practice, policy, and future research.

5.1 Interpretation of Findings

This section presents a detailed interpretation of the study's key findings, focusing on how clinicians make decisions and navigate their workflow in both traditional and AI-assisted settings. By examining the decision ladder models and thematic content analysis across different clinical scenarios, we can begin to unpack the cognitive processes, patterns, and contextual factors that shape clinical decision-making in primary care. The decision ladder diagrams offer insights into the sequence and depth of clinicians' cognitive steps, while the content analysis captures underlying themes, behaviors, and system interactions. The findings are discussed comparatively, first between Scenario 1 and 2 (both traditional EMR cases), followed by Scenarios 3 and 4 (AI-assisted cases). Each pair is analyzed to identify contrasts in reasoning style, information use, and decision efficiency. Finally, a cross-scenario synthesis integrates both ladder and thematic findings to develop a comprehensive understanding of the impact of system design on clinician cognition and workflow.

5.1.1 Decision Ladder Analysis in Scenarios 1 and 2

To begin interpreting the findings, we first analyze the decision-making workflows presented in Scenarios 1 and 2 through the lens of decision ladder models. Both scenarios utilized traditional EMRs as their primary system, but they differed significantly in terms of case complexity and depth of clinical reasoning, as captured in Figure 4-1 and Figure 4-2.

Scenario 1 depicted a complex mental health case within a traditional EMR system. The corresponding decision ladder (Figure 4-1) reveals a more layered and deliberate approach to clinical decision-making. Clinicians in this scenario demonstrated a heightened sensitivity to contextual information and patient history. The identification stage, in particular, was more prolonged and involved deeper cognitive processing. Clinicians spent time listening attentively to the patient, often for several minutes, to understand the nuanced interplay of factors contributing to the presenting symptoms.

In many instances, clinicians actively searched through patient records, looked for keywords within the EMR, and consulted SOAP note structures to guide their understanding. They measured vitals such as blood pressure and heart rate, and the history-taking process often involved probing follow-up questions. This depth translated to more thoughtful treatment planning, with clinicians weighing the consequences of various options and considering personalized, case-based care.

The execution phase also showed variability across clinicians, reflecting that mental health treatment is often nonlinear and must be tailored to each individual. Planning involved balancing pharmacological and non-pharmacological interventions, which required judgment and discussion.

Nevertheless, even in this more comprehensive workflow, certain shunts and leaps were observed:

- (*1-shunt*) Skipping detailed history-taking when the clinician was already familiar with the patient.
- (*1-shunt*) Overlooking physical causes of mental health symptoms.

- *(2-leap)* Prescribing based on prior medication success without reassessing the current context.

These shortcuts highlight the tension between clinical efficiency and thoroughness, even in complex care contexts.

In contrast, Scenario 2 involved a simpler and more structured case, urinary tract infection (UTI) management, again within a traditional EMR environment (Figure 4-2). Here, the decision-making process was significantly more streamlined. The overall workflow was rapid, with shorter identification and evaluation stages. Clinicians asked fewer follow-up questions, and many only briefly skimmed patient histories. This reflects the routinized nature of UTI diagnosis and management, particularly in female patients, where empirical treatment based on pattern recognition is common.

Some clinicians even bypassed direct interaction with the patient or overlooked urine dipstick results, assuming that standard antibiotic treatment would suffice. In these cases, consequences were considered more narrowly, focusing primarily on immediate symptom relief rather than long-term or complicating factors.

The execution phase in Scenario 2 was consistent and brief across participants. Once a UTI was identified (often through minimal questioning or quick test reviews), treatment involved a standard prescription with limited variation. Only in less typical cases, e.g., male patients or signs of complicating factors such as pregnancy or kidney stones, did clinicians pause to re-evaluate and spend more time in the room.

Importantly, Scenario 2 displayed a greater number of shunts and leaps, indicating more frequent use of cognitive shortcuts:

- *Shunt (1-a)* Skipping review of dipstick test results, often due to perceived unreliability.
- *Leap (2-a)* Using pre-visit test results as the basis for diagnosis without further clinical validation.

- *Leap (2-b)* Assuming UTIs are uncomplicated without ruling out other conditions.
- *Leap (3)* Re-prescribing previously successful antibiotics without current assessment.

This pattern raises concerns about premature closure, where clinicians arrive at a diagnosis or treatment plan too quickly without sufficient information gathering. While these shortcuts may be appropriate in routine cases, they also increase the risk of oversight, particularly when deviations from the norm occur.

While both scenarios featured instances of shunts and leaps, their frequency, nature, and implications varied considerably, highlighting the relationship between case complexity, clinician familiarity, and perceived risk. In Scenario 1, the relatively lower frequency of shortcuts was tied to the sensitive and multifaceted nature of mental health decision-making. Clinicians demonstrated greater hesitation to bypass information-gathering steps, likely due to the ambiguity and long-term consequences associated with mental health treatment. Even when shunts or leaps occurred, they often reflected relational continuity (e.g., already knowing the patient well) or clinically reasonable judgment rather than hasty oversights.

In contrast, Scenario 2 revealed a denser pattern of shunts and leaps, reflective of a routinized approach to a condition perceived as algorithmically treatable. The higher volume of shortcuts observed in this scenario suggests a degree of overfamiliarity, where clinicians rely on typical case patterns to expedite care. This is particularly evident in the way certain diagnostic steps, such as reviewing urine dipstick results or fully assessing complicating factors, were occasionally skipped or minimized. This shortcut pattern is not only a reflection of clinician behavior but also of the scenario's relative simplicity. UTIs represent a condition with well-established diagnostic and treatment templates, enabling rule-based behavior. In contrast, the mental health case lacked such structured pathways, requiring knowledge-based reasoning involving more cognitive effort, contextual judgment, and fewer predefined rules.

In summary, Scenario 1 featured a more analytical and patient-specific decision-making process, while Scenario 2 showcased a more heuristic, template-based workflow. These differences highlight how case complexity, clinical context, and system familiarity influence

not only the time spent in decision stages but also the susceptibility to shortcuts. Looking at both figures (Figure 4-1 and Figure 4-2), the progression from identification to execution becomes a lens through which we can assess decision quality, workflow demands, and potential areas for system improvement.

5.1.2 Decision Ladder Analysis in Scenarios 3 and 4

In Scenario 3 (Figure 4-3), the introduction of AI assistance to mental health case management did not fundamentally alter the overall workflow structure identified in Scenario 1. However, several meaningful shifts occurred, primarily in terms of increased cognitive demands related to assessing and integrating AI-generated insights. Clinicians were tasked with reviewing additional information, such as AI-generated summaries of patient histories and suggested clinical outcomes, as well as interpreting confidence scores and standardized assessments like GAD and PHQ scores.

In the identification phase, clinicians notably added a step of verifying whether AI suggestions aligned with their own clinical judgment. This reflective cross-check served as an additional safeguard, ensuring that AI advice did not unintentionally bias clinical reasoning. In assessing the system state, clinicians explicitly considered whether AI recommendations were based on sufficient, accurate data, and critically evaluated the reliability and meaningfulness of the AI's confidence scores.

The most pronounced changes occurred in the consequence prediction and evaluation of options stages. Clinicians were highly conscious of the potential ramifications of either accepting or dismissing AI suggestions. They actively weighed the risks of overprescribing or inappropriate referrals against the potential efficiency benefits that AI-generated notes could offer. Concerns about patient trust and quality of care were paramount, prompting clinicians to consider carefully whether to accept, modify, or reject AI suggestions on a case-by-case basis. Thus, even with AI integration, clinicians sought to maintain a patient-centered approach and preserve their professional autonomy.

The execution phase particularly benefited from AI, with significant efficiency gains observed in administrative tasks such as generating SOAP notes and automating referral processes. Clinicians appeared comfortable delegating these lower-risk administrative responsibilities to AI, enabling them to focus more intensively on clinical reasoning and patient interactions. Only one notable shortcut, specifically a shunt, emerged clearly in this scenario: clinicians frequently deferred to AI for lab result analyses, effectively reducing their cognitive workload and allowing for quicker data interpretation and decision-making.

Scenario 4 (Figure 4-4) demonstrated the clearest and most positive impact of AI integration, given the algorithmically treatable nature of the clinical condition (UTI diagnosis and treatment). With AI's support, the clinical workflow became significantly more streamlined and straightforward, closely aligning with the already routinized approach clinicians used in Scenario 2.

Within the identification phase, clinicians again incorporated steps to ensure alignment between AI recommendations and their own clinical judgments. Here, however, they specifically considered whether symptoms genuinely indicated an uncomplicated UTI or potentially represented another condition mimicking a UTI. Evaluating the system state involved similar cognitive tasks as Scenario 3: clinicians assessed whether AI recommendations had sufficient data backing and scrutinized the confidence scores to determine the validity of the AI-generated advice.

The consequences of either following or disregarding AI recommendations were evaluated more explicitly than in traditional EMR cases. Clinicians were mindful of the broader implications, such as antibiotic resistance risks and impacts on patient trust. They also considered the effect of AI-generated documentation on workflow efficiency. In the evaluation of options stage, decisions on whether to accept, modify, or reject AI input became routine but critical considerations. Many clinicians embraced the practical benefit of using AI for medication selection and charting.

In the execution phase, clinicians actively employed AI suggestions to prescribe antibiotics, reflecting increased reliance on AI-generated treatment plans. They frequently made minor edits to AI-generated notes to more precisely align documentation with their clinical insights. Nonetheless, two distinct leaps emerged clearly:

- *Leap (4)*: Accepting AI-suggested antibiotic prescriptions without extensive patient re-assessment, due to familiarity and confidence in AI-generated outcomes.
- *Leap (5)*: Adopting AI-generated clinical notes with minimal edits or clinical judgment adjustment, reflecting trust in AI's documentation accuracy.

Overall, Scenario 4 highlights AI's greatest strengths: enhancing workflow efficiency, accelerating decision-making, and reducing administrative burden, provided the clinical context is clearly defined and the recommendations straightforward.

Comparing Scenario 3 and Scenario 4 reveals that AI's integration into clinical workflows is highly context-dependent. In the complex mental health scenario (Scenario 3), clinicians cautiously integrated AI support, emphasizing the importance of maintaining professional judgment and patient-centered care. AI's main benefit lay in administrative efficiency, with clinicians actively scrutinizing AI recommendations for potential biases or inaccuracies. Conversely, in the straightforward UTI scenario (Scenario 4), clinicians embraced AI assistance more readily, showing greater trust in its algorithmically driven recommendations.

These differences underscore the critical need for AI system designs that adapt to clinical complexity and clinician cognitive strategies, balancing autonomy with intelligent assistance. Such adaptability can optimize both clinician experience and patient outcomes, aligning AI recommendations with the context-specific nature of clinical practice.

5.1.3 Comparative Synthesis of Traditional vs. AI-Integrated Decision Ladders

Analyzing both traditional and AI-integrated scenarios through decision ladders has provided significant insights into how clinical workflows and cognitive processes evolve in response

to advanced decision-support technologies. Overall, the integration of AI within clinical decision-making distinctly impacted clinician cognition, workflow efficiency, and the propensity for cognitive shortcuts such as shunts and leaps.

In traditional EMR scenarios (Scenarios 1 and 2), clinician decision-making varied significantly depending on case complexity. Complex scenarios, such as mental health assessments, elicited deeper cognitive engagement, a thorough exploration of patient histories, and fewer cognitive shortcuts. Conversely, simpler, more routine scenarios, like diagnosing and treating uncomplicated UTIs, prompted more frequent and potentially risky cognitive shortcuts, characterized by rapid, heuristic-based decision-making. Although these shortcuts generally contributed positively to efficiency, they raised concerns about premature closure, especially in atypical cases.

Introducing AI assistance (Scenarios 3 and 4) reshaped clinician workflow in meaningful ways. The presence of AI-generated recommendations, summaries, and confidence scores initially increased cognitive load during identification and evaluation stages, as clinicians validated AI suggestions against their clinical judgments and assessed the reliability of AI outputs. This additional step reflects cautious but essential verification processes, indicating that clinicians maintained their professional autonomy despite adopting advanced tools.

Notably, the integration of AI significantly influenced clinician efficiency and the distribution of cognitive effort across clinical workflows. AI support positively impacted administrative and documentation tasks, substantially reducing clinicians' administrative burdens by automating SOAP notes, charting, and referral processes. In straightforward, algorithmically manageable scenarios (e.g., UTIs), clinicians quickly developed trust in AI recommendations, demonstrated through a notable increase in cognitive leaps. In contrast, in more complex and less predictable contexts, such as mental health, clinicians remained conservative, carefully examining the alignment between AI outputs and clinical reasoning.

The comparative synthesis highlights a crucial insight: AI integration is most effective when it aligns with the clinical scenario's cognitive complexity and the clinician's confidence in

algorithmic predictability. Routine clinical scenarios benefit from AI's streamlined, structured approach, resulting in reduced cognitive workload and enhanced efficiency. However, complex cases require cautious AI integration, necessitating careful design that emphasizes interpretability, transparency, and clinician autonomy.

5.1.4 Content Analysis in Scenarios 1 and 2

The content analysis for Scenarios 1 and 2 provides an understanding of how clinicians navigate decision-making in traditional EMR settings. A central theme across both scenarios is the dominant reliance on clinician expertise and personal judgment, often shaped by their experience, familiarity with the patient, and contextual cues.

In Scenario 1 (a complex mental health case), the data shows clinicians devoting significant time to understanding the patient's broader context, including psychosocial factors, previous diagnoses, medication history, and subjective cues like emotional tone or patient demeanor. This patient-centered approach often required clinicians to manually extract relevant information from EMRs or recall previous interactions. Descriptions highlighted the importance of gathering a holistic view of the patient rather than rushing to diagnosis or treatment. Mental health visits were described as situations where each case is unique and not easily reducible to standardized protocols. Clinicians felt that automation and rigid structures failed to capture the emotional nuance and human connection essential to such visits.

Scenario 2 (a simpler UTI case), by contrast, showcased a more streamlined, protocol-driven workflow. Clinicians often used heuristic reasoning to make quick decisions based on symptom patterns or patient demographics. Many were comfortable relying on past treatment outcomes or pre-visit test results, especially in female patients where UTIs are common and often uncomplicated. However, this efficiency came with potential trade-offs: the content reveals several instances where clinicians skipped reviewing dipstick results or physical symptoms in detail. This demonstrates a reliance on pattern recognition and assumption-based shortcuts, which, while efficient, may overlook critical nuances in edge cases (e.g., male patients or recurring infections).

Other findings include the following:

- **Shunting Documentation:** Clinicians frequently postponed documentation or relied on structured templates (such as copying previous notes or utilizing auto-text), which sometimes resulted in incomplete or overly generic records. While this approach saved time, it introduced risks related to data accuracy, particularly when documentation was updated retrospectively.
- **Cognitive Burden in Complex Cases:** In the absence of structured decision support, clinicians had to manage the full weight of clinical reasoning, documentation, and patient interaction simultaneously. This considerable cognitive workload was especially evident during mental health visits, where decisions were nuanced and emotionally demanding.

In both scenarios, while clinicians were confident in their clinical judgment, the lack of structured support systems required constant balancing between thoroughness and efficiency, especially under time constraints.

5.1.5 Content Analysis in Scenarios 3 and 4

Scenarios 3 and 4 introduce AI-enabled systems into the clinical workflow, and the content analysis reveals a nuanced shift in clinician behavior, not necessarily replacing human judgment, but reshaping how decisions are made, supported, and documented.

In Scenario 3 (AI-assisted mental health care), clinicians described AI as a "second set of eyes", a tool to validate their impressions, reduce error, and enhance documentation.

However, their overall approach to the patient remained deeply human-centered.

Descriptions revealed that clinicians were cautious about integrating AI-generated suggestions directly into decision-making. Many reviewed AI outputs such as confidence scores, summary notes, or PHQ/GAD scores but used them as reference points rather than direct inputs. There was a strong emphasis on retaining professional autonomy and ensuring that AI outputs aligned with their own clinical reasoning. This reflects a broader concern about the limitations of AI in emotionally complex or context-sensitive cases.

Moreover, clinicians voiced ethical and interpersonal concerns, including fear of undermining the human-to-human connection, worries about legal accountability, and uncertainty about AI accuracy in subtle, non-algorithmic scenarios. In several cases, clinicians reported intentionally avoiding use of AI during the patient interaction itself, preferring to rely on AI outputs before or after the visit to preserve empathy and trust.

Scenario 4, dealing with AI-assisted UTI cases, presented a contrasting picture. Here, AI was widely embraced due to the routine and structured nature of the clinical problem. Clinicians reported using AI to pre-populate referral fields, suggest treatment plans, and generate prescription notes. Many chose to edit AI-generated outputs rather than write from scratch, thus saving time without sacrificing control. Trust in AI was higher in this scenario, and workflow efficiency was substantially improved.

Importantly, the data suggests that clinicians differentiated between administrative and clinical domains when deciding how much to rely on AI. Administrative tasks (e.g., scribing, referrals, note-taking) were delegated to AI, whereas final clinical decisions were still seen as the clinician's responsibility. However, in straightforward cases, some clinicians described a growing comfort in prescribing directly based on AI suggestions, indicating a gradual shift in trust when the condition matched well-defined criteria.

Emerging themes from Scenarios 3 and 4 include:

- **Adaptive trust in AI:** Clinicians adjusted their reliance on AI based on the perceived complexity and risk of the case. This trust was often conditional, grounded in how well AI aligned with their judgment and whether it supported (rather than replaced) their reasoning.
- **Efficiency through augmentation:** AI systems were praised for reducing information overload, especially by surfacing relevant history or suggesting standardized actions. This freed up clinicians to focus on patient communication and complex decision points.

- **Cautious integration in sensitive domains:** Mental health care continued to resist full AI adoption due to the relational, emotional, and legally sensitive nature of the work. Clinicians emphasized the importance of discretion and personalization that AI systems could not yet match.

5.1.3 Comparative Synthesis of Traditional vs. AI-Integrated Content Analysis

Comparing traditional and AI-integrated workflows reveals a clear shift in the distribution of cognitive effort and task delegation. In traditional workflows, clinicians were central actors in all decision stages, from information gathering and interpretation to documentation and communication. These tasks required sustained cognitive load and often resulted in variation in practice, particularly when time constraints encouraged the use of shunts and leaps.

With AI integration, workflows became more structured and modular. AI systems absorbed some of the cognitive and administrative load, particularly in information retrieval, note generation, and guideline-based treatment suggestions. Clinicians' cognitive roles evolved from that of the sole decision-maker to a critical evaluator and adaptive integrator, assessing AI's relevance, interpreting its confidence levels, and contextualizing outputs within patient preferences.

However, this transition also brought new challenges. Clinicians needed to develop a sense of when to trust AI, when to override it, and how to communicate AI-supported decisions to patients in a transparent and ethical manner. The integration of AI introduced a new cognitive task: evaluating the evaluator, judging the adequacy of AI insights before acting on them.

Notably, the scenarios demonstrate that AI's impact is not uniform; it is shaped by the complexity of the clinical context and the clinician's level of trust. While AI flourished in structured, low-risk scenarios like UTIs, its role remained limited in emotionally complex or highly individualized contexts like mental health care.

In essence, AI is not simply a tool to make decisions faster, it is a collaborator that reshapes how decisions are made, requiring new skills, new workflows, and a rebalancing of clinical cognition between humans and machines.

5.1.6 Integrated Findings: Synthesizing Decision Models and Thematic Insights

To develop a comprehensive understanding of how clinical decision-making is shaped by both traditional and AI-integrated systems, this section synthesizes insights from the decision ladder analysis and thematic content analysis. While each method independently revealed meaningful patterns, their integration offers a more holistic view of clinician cognition, behavior, and system interaction in real-world settings.

1. Complexity as a Primary Driver of Clinical Behavior

- a.** Across both analytical approaches, case complexity consistently emerged as a key determinant of clinician behavior. In more complex cases, such as mental health scenarios, clinicians displayed deeper engagement with patient context, spent more time in the identification and interpretation phases, and were more cautious in accepting system-generated suggestions, whether from a traditional EMR or an AI-augmented platform. This was reflected in the decision ladders through longer deliberation paths and fewer leaps, and in the content analysis through rich narratives of emotional, legal, and interpersonal considerations.
- b.** In contrast, simpler, algorithmically treatable cases like UTIs prompted more standardized workflows, higher rates of shortcuts, and greater openness to automation. The ladders in these scenarios were shorter and more direct, with more frequent shunts and leaps. Clinicians in content narratives expressed comfort with using AI to expedite decisions in these cases, particularly when supported by lab results or prefilled clinical summaries.

2. Shifts in Cognitive Load and Decision Roles

- a. A consistent theme across both analyses is the redistribution of cognitive effort with the introduction of AI. In traditional systems, clinicians carried the full cognitive burden, navigating patient context, making diagnostic judgments, recording decisions, and maintaining interpersonal rapport simultaneously. This was particularly evident in the mental health cases, where decision ladders were deep, and content reflected clinician fatigue, time pressure, and emotional labor.
- b. With AI integration, this burden shifted. AI tools supported data retrieval, documentation, and treatment suggestion, particularly in the earlier stages of decision-making. This shift was visible in the decision ladders as changes in the system state and execution stages, and thematically through clinicians' comments on AI's role in handling administrative tasks, surfacing red flags, or generating referral templates.
- c. However, this cognitive delegation was selective and context-sensitive. Clinicians retained final authority, often editing AI outputs and using them as optional supports rather than definitive answers. In complex cases, AI tools were framed more as "second sets of eyes" than decision-makers.

3. Clinician Autonomy, Trust, and Control

- a. Both methods revealed strong themes of professional autonomy and conditional trust in AI. Decision ladders showed that even when AI outputs were available, clinicians often evaluated whether they aligned with their own reasoning before acting. In content analysis, clinicians articulated a need to retain control, especially when facing high-risk or emotionally sensitive scenarios.
- b. Trust in AI was shown to be highly contingent on the task domain: clinicians trusted AI for documentation, scribing, and structured data interpretation, but were more skeptical when AI offered treatment or

diagnostic suggestions, especially when those suggestions lacked explainability or contradicted clinician intuition.

- c. Importantly, clinicians expressed discomfort with overreliance on AI. Some feared legal or ethical consequences of blindly following AI recommendations, while others felt that relying too heavily on AI might erode the human connection central to care delivery, particularly in mental health settings.

4. Structural Consistency vs. Personalization

- a. Another core tension that emerged across both analyses was the balance between structured system logic and the need for individualized care. In traditional workflows, clinicians were free to personalize interactions but risked inconsistency and reliance on memory. In AI-augmented workflows, structure and efficiency improved, but clinicians sometimes resisted the rigidity of AI logic, especially when it didn't reflect patient-specific nuances.
- b. This was evident in the ladders (e.g., shorter paths in AI scenarios) and in thematic findings where clinicians expressed concern that AI systems "don't know the patient like I do." Even in streamlined scenarios like Scenario 4, clinicians often modified or reviewed AI-generated outputs before finalizing them.

5. AI's Role: Efficiency Partner, Not Clinical Authority

- a. Finally, both methods support the view that clinicians do not see AI as a replacement, but rather as an efficiency partner, useful for reducing documentation burden, organizing information, and surfacing potentially overlooked factors. In complex cases, AI served as a safety net rather than a guide. In simple cases, it expedited processes while still leaving room for clinician oversight.

- b. The key insight is that its technical accuracy does not simply determine AI's effectiveness but by how well it fits into clinicians' mental models and workflows. AI that supports without intruding, structures without constraining, and enhances rather than replaces human reasoning is more likely to be accepted and used meaningfully.

5.2 User-Centered Design Considerations

The findings of this study reinforce the importance of grounding AI-augmented health technologies in user centered design principles that prioritize the cognitive, emotional, and contextual needs of clinicians. Based on observed decision-making patterns and thematic insights, several key design considerations emerge:

1. Support, Don't Supplant Clinical Judgment

Clinicians consistently framed AI as a support tool rather than a decision-maker. Systems should be designed to augment human reasoning, not replace it. Interfaces must clearly indicate:

- a. How AI reached a recommendation (e.g., contributing factors, thresholds met).
- b. The degree of certainty (e.g., confidence score with meaningful context).
- c. Options for clinicians to accept, reject, or modify suggestions easily.

2. Preserve Human-to-Human Interaction

Especially in complex and emotionally sensitive cases (e.g., mental health), clinicians were concerned that AI could interfere with the therapeutic relationship. Design features should:

- a. Allow clinicians to review AI outputs before or after the encounter, not during it.
- b. Emphasize empathetic communication support rather than intrusive prompts.
- c. Provide clinician-controlled AI transparency (e.g., whether or how AI suggestions are shared with patients).

3. Adaptive Complexity Based on Case Type

The level of AI involvement and the structure of system outputs should be context-aware. For example:

- a. In high-variability cases, present AI outputs as flexible suggestions.
- b. In straightforward cases (e.g., uncomplicated UTIs), allow more automation (e.g., auto-filled prescriptions with review).
- c. Avoid overly rigid workflows that don't adapt to patient-specific needs.

4. Enable Quick and Meaningful Interaction with the Interface

Clinicians preferred tools that saved time, reduced clicks, and surfaced relevant information quickly. Design considerations include:

- a. Summarized patient histories with interactive drill-downs.
- b. Auto-populated fields with clear provenance.
- c. Smart defaults that can be overridden without penalty.

5. Transparency and Legal Confidence

Clinicians voiced concerns about legal liability when following AI recommendations. Interfaces should:

- a. Log decision paths and interactions for auditability.
- b. Indicate which parts of the chart or history informed a recommendation.
- c. Provide alerts when critical omissions or inconsistencies exist.

6. Respect Clinical Autonomy and Workflow Variability

Design should reflect that not all clinicians work the same way. UCD should account for:

- a. Configurable workflows or display modes (e.g., timeline view, card view).

- b.** Support for different specialties or roles (e.g., nurse practitioners vs. physicians).
- c.** Avoiding alert fatigue or forcing a fixed sequence of steps unless required for safety.

5.3 Recommendations for Practice

Building on the insights from both the decision ladder models and thematic content analysis, this section presents recommendations for improving clinical workflows, system integration, and practitioner engagement with AI-augmented health technologies. These recommendations are intended for healthcare organizations, designers, clinical leaders, and implementation teams seeking to adopt AI-based tools responsibly and effectively.

1. Align AI Integration with Clinical Context and Complexity

AI systems should be selectively integrated based on the complexity of the clinical task:

- a.** Use high-autonomy AI for routine, protocol-based conditions (e.g., uncomplicated UTIs), where automation can reduce clinician burden without compromising care.
- b.** Use low-autonomy, clinician-in-the-loop models for complex, context-rich cases (e.g., mental health), where judgment and personalization are essential.

2. Implement AI as a Collaborative Tool, Not an Authority

AI tools should be introduced as collaborators that offer structured suggestions, not directives. Practice leaders and educators should:

- a.** Emphasize the role of AI as a second opinion or assistant.
- b.** Avoid framing AI as a replacement for clinician decision-making.
- c.** Encourage clinicians to validate and interpret AI outputs, fostering a healthy level of skepticism and reflection.

3. Prioritize Training for AI Literacy and Responsible Use

To ensure safe and confident adoption of AI systems, institutions must invest in training clinicians on:

- a. Understanding how AI models are built, their limitations, and sources of bias.
- b. Interpreting outputs like confidence scores and suggested treatments.
- c. Recognizing when to override AI recommendations and how to document clinical rationale.

AI literacy should be treated as a core competency, much like evidence-based medicine or ethical decision-making.

4. Establish Ethical, Legal, and Documentation Safeguards

Given clinician concerns around accountability and documentation, healthcare institutions should:

- a. Ensure systems maintain an auditable record of AI interactions and clinician edits.
- b. Provide clear institutional policies about clinician responsibility when using AI.
- c. Avoid black-box models unless their reasoning is transparently presented to users.

5. Create Feedback Loops for Continuous Improvement

Clinicians should have ways to flag AI errors, inconsistencies, or successes to improve the system over time. Practices should:

- a. Embed in-system feedback buttons or passive monitoring features.
- b. Encourage post-implementation debriefs and surveys to capture insights.
- c. Regularly update the AI model based on real-world usage patterns.

Making clinicians part of the improvement cycle not only enhances performance but strengthens engagement and trust.

6. Foster a Culture That Values Human Judgment and Empathy

Organizations must maintain a cultural foundation that celebrates clinician expertise and the human aspects of care, even in the face of increasing automation. This includes:

- a. Encouraging time for patient communication and narrative collection, especially in emotionally sensitive domains.
- b. Designing workflows that do not penalize clinicians for choosing to override AI.
- c. Emphasizing values like compassion, communication, and shared decision-making in training and evaluation.

Ultimately, successful AI integration is not just about efficiency , it's about supporting clinicians in delivering care that is both informed and humane.

5.4 Challenges and Limitations of the Study

While this study provides insights into clinical decision-making across traditional and AI-integrated systems, several limitations must be acknowledged regarding its methodology, scope, and analytical approach.

1. Secondary Data Use

This analysis relied on a pre-existing dataset originally collected under a different researcher's protocol. While the data was rich and allowed for novel insights, the inability to probe deeper, clarify responses, or tailor follow-up questions in real time constrained opportunities for more nuanced understanding.

2. Scenario-Driven Constraints

The study employed fixed clinical scenarios to enable standardized comparison across participants. While this increased internal consistency, it limited realism. Clinicians could not

adapt dynamically to patient variability or unexpected complexities, factors that often shape real-world decision-making. Additionally, the number of scenarios was limited, and the cases selected represented two extremes: one very routine (uncomplicated UTI) and one highly sensitive (mental health distress). This binary contrast, while analytically useful, may not reflect the full spectrum of clinical complexity. Future work should explore more nuanced, mid-complexity scenarios, such as chronic condition management, multimorbidity, or ambiguous presentations, that may elicit different decision strategies and uses of AI.

3. Sequence Bias

All participants encountered the clinical scenarios in the same sequence (e.g., complex followed by simple), potentially introducing sequence effects. Clinicians may have become more comfortable with the interface over time or mentally adapted to the interview structure, influencing how they approached later scenarios.

4. Small and Region-Specific Sample

The participant pool included 14 clinicians from Ontario, Canada, spanning various practice models. While diverse in experience, the small sample size and regional specificity limit the generalizability of findings to other healthcare systems or cultural contexts. In addition, participants likely shared similar experiences with EMRs and exposure to AI-enabled tools, which may have shaped their expectations and interactions in ways that differ from clinicians in other regions or health systems.

5. Limited AI Exposure

The AI-enhanced interface presented to participants was a mock-up, not a fully interactive, production-level tool. As a result, clinicians' feedback reflected anticipated reactions and assumptions, rather than lived experiences or long-term interactions with AI systems in practice.

6. No Audio Recordings or Real-Time Observations

Only transcripts were available for analysis. The absence of audio recordings limited the ability to interpret tone, hesitation, emphasis, or emotional expression, factors that are often telling in understanding cognitive and affective states. Similarly, timing data (e.g., how long clinicians spent on each step) could not be captured.

7. Subjectivity in Content Analysis

The thematic coding process, while grounded in rigorous qualitative methodology, is inherently interpretive. Researcher bias may influence theme extraction, especially when coding for abstract constructs like trust, autonomy, or cognitive shortcuts.

8. Interpretation of Cognitive Shortcuts

The identification of shunts and leaps was based on retrospective transcript analysis, not direct observation of real-time behavior. Although these were framed within the decision ladder model, assigning cognitive processes post hoc carries the risk of over-interpretation or confirmation bias. This also lead to approximate frequency estimation. The counts presented are based on qualitative coding of interview and observation data. Not all shortcuts were explicitly verbalized by participants, and some behaviors were inferred, making the numbers approximate rather than exact.

9. Single Interface Context

All scenarios were conducted using the TELUS Health Bed prototype interface. While informative, findings may not transfer directly to other EMR or AI platforms, limiting interface-specific generalizability.

10. Potential Interviewer and Response Bias

The original interviews were conducted by a single researcher, which may have influenced how participants responded. Additionally, some clinicians may have framed their answers to reflect what they perceived as the study's goals or social desirability norms, especially when discussing AI.

5.5 Future Research Directions

This study lays the groundwork for deeper inquiry into AI-supported clinical decision-making. Several key directions are recommended for future exploration:

1. Real-Time AI Interaction Studies

Future work could include live observational studies or think-aloud protocols, where clinicians interact with fully functional AI-EMR systems in real clinical environments. This would enable the capture of authentic decision-making processes, interruptions, and information flow.

2. Longitudinal Evaluation of Trust and Adaptation

Research could examine how clinicians' trust in AI evolves over time, particularly with repeated use. Does early skepticism diminish with familiarity? Do initial overreliance patterns self-correct? Understanding the temporal dynamics of adoption is crucial for effective system rollout.

3. Patient Inclusion and Triadic Interaction Analysis

Given the increasing emphasis on shared decision-making, future studies should incorporate the patient voice. This includes examining how visible AI use affects patient trust, clinician-patient communication, and triadic dynamics in consultations.

4. Cross-Setting and Cross-Specialty Studies

Extending this research beyond primary care to specialties such as emergency medicine, oncology, or psychiatry could uncover unique adoption challenges, documentation needs, or cognitive demands specific to each field.

5. Co-Design Studies with Clinicians

Engaging clinicians directly in iterative co-design of AI features, such as editable summaries, explainable confidence scores, or visual risk indicators, could lead to more usable and interpretable systems that align with actual workflows and needs.

6. Quantitative Mapping of Cognitive Workload

To complement qualitative findings, future studies should use tools like NASA-TLX, eye-tracking, or clickstream analysis to objectively measure how AI impacts cognitive load, decision latency, attention distribution, and task switching.

7. Ethical and Legal Preparedness Frameworks

Further work is needed to co-develop ethical, legal, and governance frameworks that account for responsibility-sharing between clinicians and AI systems. Research should explore consent models, audit trails, and accountability standards in AI-augmented environments.

In summary, this chapter offered a detailed exploration of how AI integration into EMRs reshapes clinician decision-making across different clinical scenarios. Through the use of decision ladders and content analysis, it was uncovered how AI influences workflows, trust dynamics, and cognitive strategies, particularly distinguishing between simple and complex cases. While AI shows promise in supporting administrative and low-risk tasks, its role remains carefully curated by clinicians who prioritize autonomy, empathy, and context sensitivity in their care. These findings underscore the importance of designing AI tools that are not only technically accurate but also aligned with the cognitive and ethical realities of clinical work. As primary care continues to evolve, it is essential that AI systems are developed to complement, not replace, human judgment. This work contributes to that vision by offering grounded insights into the nuanced interplay between clinicians and AI in real-world settings.

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