Thesis

Improving Patient Outcomes through Dual-Process Theory: A Framework for a Clinical Decision Support System empowering Junior Doctors

submitted by

Alexander Frauenschuh, MBA

in partial fulfilment of the requirements for the degree of

Doktor(in) der gesamten Heilkunde

(Dr.(in) med. univ.)

at the

Medical University of Graz

executed at the

Clinical Institute for Medical and Chemical Laboratory Diagnostics

under the supervision of

Priv.-Doz. Dr. med. univ. Dietmar Enko, MBA LL.M.

Dr. med. univ. Simon Michaelis

Graz, 29.05.2023

I Declaration of Academic Integrity

I hereby confirm that the present diploma thesis is the result of my own independent scholarly work. I also confirm that in all cases, where material from the work of others (in books, articles, essays, dissertations, and on the internet) is acknowledged, quotations and paraphrases are clearly indicated. No material other than that cited in the reference list has been used. I have read and understood the Medical University's regulations and procedures concerning plagiarism.

Graz, 29.05.2023 Alexander Frauenschuh, m.p.

II Table of contents

III Abbreviations and their meanings

AI	Artificial Intelligence
CDSS	Clinical Decision Support System(-s)
CPOE	Computerized Physician Order Entry
DDI	Drug-Drug Interaction
DDSS	Diagnostic Decision Support System(-s)
DMSS	Decision-Making Support System(-s)
DPT	Dual-Process Theory
ECG	Electrocardiogram
ED	Emergency Department
EDDS	Electronic Drug Dispensing System(-s)
EHR	Electronic Health Record
i-DSS	Intelligent Decision Support System(-s)
ML	Machine Learning
PHR	Personal Health Record
SNOMED	Systematized Nomenclature of Medicine

IV Title and Summary in German

Verbesserung der Patientenergebnisse durch die Dual-Prozess Theorie: Ein Framework für ein klinisches Entscheidungsunterstützungssystem zur Unterstützung von jungen Ärztinnen und Ärzten

Diese Arbeit untersucht die Anwendung der Dual-Prozess Theorie auf den Entscheidungsfindungsprozess von jungen Ärztinnen und Ärzten in Notaufnahmen. Da Fehler im Diagnoseprozess zu verheerenden Patientenergebnissen führen können, ist es von entscheidender Bedeutung, diesen zu verstehen und mögliche Optimierungen mittels Informationstechnologie zu erforschen. Daher wurde eine semi-strukturierte Literaturrecherche, welche ausgewählt wurde, um das breites Themenspektrum abdecken zu können, durchgeführt. Die Suche fand über PubMed und Google Scholar statt und ergab 75 Artikel, von denen 37 als relevant erachtet und daher einbezogen wurden. Zusätzlich wurden drei in diesen Artikeln zitierte Ressourcen aufgrund ihrer bedeutenden Erkenntnisse integriert. Die Dual-Prozess Theorie hilft, den Diagnoseprozess zu verstehen, indem sie zwei Denkweisen identifiziert: System 1, das schnell, intuitiv und energieeffizient, und System 2, das langsamer, analytisch und anspruchsvoller in Bezug auf kognitive Ressourcen ist. Da System 1 viel Erfahrung erfordert, um gut zu funktionieren, neigen jungen Ärztinnen und Ärzten dazu, sich auf das Denken im System 2 zu verlassen. Dieses System kann jedoch, insbesondere unter hohem Stress, kognitive Ressourcen verbrauchen, was zu kognitiver Überlastung und anschließend zu diagnostischen Fehlern führen kann. Diese Arbeit schlägt ein Framework vor, wie ein speziell entwickeltes klinisches Entscheidungsunterstützungssystem die kognitive Belastung durch das Abbilden wahrscheinlicher Differentialdiagnosen mit den dazugehörigen Untersuchungsverfahren verringern könnte. Ein solches System könnte jungen Ärztinnen und Ärzten bei ihrer Entscheidungsfindung helfen und so die Patientenergebnisse verbessern. Obwohl dieses Framework vielversprechend ist, bleibt es theoretisch. Zukünftige Forschung sollte sich auf die Entwicklung und Testung eines solchen Modells in realen klinischen Umgebungen konzentrieren, um die Performance und Auswirkung genau bewerten zu können.

V Abstract

This thesis examines the application of dual-process theory to the decision-making process of junior doctors in emergency departments. Since errors in the diagnostic process can lead to devastating patient outcomes, comprehending the formation of diagnoses and exploring potential enhancements through information technology is essential. As such, a semi-structured literature search, selected for its ability to encompass a wide range of topics, was conducted across PubMed and Google Scholar. The search yielded 75 papers, of which 37 were deemed relevant and therefore included. Additionally, three resources cited within these papers were also incorporated due to their significant insights. The dual-process theory helps explain the diagnostic process by identifying two modes of thinking: System 1, which is rapid, intuitive, and energy-efficient, and system 2, which is slower, analytical, and more demanding of cognitive resources. Since system 1 requires much experience to work well, junior doctors tend to rely on system 2 thinking. However, this system, especially when employed under high stress, can deplete cognitive resources, leading to cognitive overload and subsequent diagnostic errors. This thesis proposes a framework for how a specifically designed clinical decision support system might reduce cognitive load by suggesting probable differential diagnoses and recommended testing procedures. Such a system could help junior doctors with their decision-making, thereby improving patient outcomes. While this framework provides a promising outlook, it remains theoretical. Future research should focus on the development and testing of such a model in real-world clinical settings to accurately evaluate its performance and impact.

1 Introduction

The health care system has long suffered from a glaring blind spot: diagnostic errors, which persist across all care settings and continue to harm an unacceptable number of patients. For example, the American Committee on Diagnostic Error in Health Care provided a cautious estimate, which stated that 5% of U.S. adults who seek outpatient care each year experience a diagnostic error. Research conducted over several decades through post-mortem examinations revealed that about 10% of patient deaths can be attributed to diagnostic errors. Furthermore, analysis of medical records indicates that these errors are responsible for 6 to 17% of adverse events in hospitals. Furthermore, diagnostic errors not only are the leading type of paid medical malpractice claims, but they are also nearly twice as likely to result in the patient's death compared to other types of claims. Based on their research results, the committee on diagnostic error in health care estimated that most people will experience at least one diagnostic error in their lifetime, sometimes with devastating consequences (Committee on Diagnostic Error in Health Care et al., 2015, p. 1). This disproportionate high share of diagnostic errors has also been found in a startling study conducted in Japan: It uncovered that a staggering 68.5% of the screened error cases were due to errors in the diagnostic process (Miyagami et al., 2023, p. 342). Medical errors, especially those involving the diagnostic process, pose a significant threat to patient safety (Raharjanti et al., 2021, p. 6), which is why it is crucial to address this issue as it greatly influences patient outcomes (Baartmans et al., 2022, p. 1139). The urgency of addressing this problem cannot be overstated, as the implications of these errors are profound and far-reaching.

In the light of these alarming statistics, this thesis aims to identify potential vulnerabilities in the diagnostic process with the focus on junior doctors in emergency departments (EDs) and develop a theoretical framework for the targeted application of clinical decision support systems (CDSS) to reduce clinical errors. A semi-structured literature search will be conducted, with findings discussed in Chapters 3 to 5.

Chapter 3 will introduce dual-process theory (DPT), a widely accepted theory among cognitive scientists (Brosnan et al., 2016, p. 2116) that explains human decision-making through two systems, using the framework established by Nobel Laureate Daniel Kahneman. In Chapter 4, DPT will be applied to clinical reasoning, exploring differences in reasoning among junior doctors compared to their experienced colleagues, as well as the unique challenges of emergency departments. Concluding the chapter, an analysis of sources of clinical errors in the diagnostic process will be provided. Finally, Chapter 5 will present an overview of clinical decision support systems and, using the knowledge gained from previous chapters, elaborate on a theoretical framework for designing a CDSS specifically tailored to improve the decision-making process of junior doctors in emergency departments.

To guide the investigation, the following research questions have been formulated:

1. How can dual-process theory be applied to explain clinical reasoning in medical decision-making?
    a. What are the differences in decision-making between experienced and junior doctors?
    b. What are the specific challenges regarding clinical reasoning in emergency departments?
    c. What are the sources of diagnostic errors in the clinical reasoning process?
2. How might a specifically designed clinical decision support system assist junior doctors in emergency departments with their diagnostic reasoning?

By combining concepts from medicine, psychology, and computer science, the author hopes to contribute to the overarching goal of reducing clinical errors and ultimately improving patient outcomes.

2 Methodology

To address the research question, a comprehensive semi-structured literature search was undertaken, primarily utilizing PubMed and supplemented with Google Scholar to explore the non-medical aspect of the dual-process theory. The semi-structured literature search approach was selected due to the wide range of topics encompassed within the scope of this research. For the purposes of this thesis, gaining a broad understanding of multiple subjects is prioritized over an in-depth exploration of a single topic. Acquiring insights from various fields is essential for effectively answering the research questions. To achieve this, multiple search strings were employed to pinpoint pertinent literature. In PubMed, the search strings included: "Dual-process Theory AND clinical reasoning," "Clinical Reasoning AND junior doctors," "Clinical Reasoning AND emergency unit," "Diagnostic errors AND emergency department," and "Clinical decision support systems." Meanwhile, a single search string was applied in Google Scholar: "Dual-process theory." For all search queries, the top 10 abstracts were examined, with the exception of "Clinical reasoning AND emergency unit," where the initial results were insufficient; consequently, the first 25 results were assessed. The majority of searches were filtered by publication date, focusing on the range of 2009 to 2023, to emphasize relatively recent research. The sole exception was the "Clinical decision support systems" search string, for which only reviews and systematic reviews were considered, and the date range was narrowed to 2018-2023. Given the rapidly evolving nature of clinical decision support systems, prioritizing recent literature was deemed crucial.

The search yielded 75 articles, with their abstracts subsequently reviewed. After assessing the abstracts for their relevance in addressing the research question and eliminating duplicates, 37 articles were selected for inclusion. In addition, three resources cited by at least one of the discovered papers were incorporated, as they appeared to offer valuable insights and were thus considered highly relevant to answering the research question. Consequently, the search process culminated in a total of 40 papers being incorporated into the analysis.

This paper's structure is designed to prioritize readability while maintaining a logical organization. Drawing inspiration from the classic IMRaD (Introduction, Methods, Results, and Discussion) format, the results are presented in chapters 3 through 5.1, with each chapter focusing on a distinct topic. First, dual-process theory is explained as a general concept. Then, clinical reasoning in the light of dual-process theory is elaborated. This chapter also includes the specifics of junior doctors and emergency departments, as well as an explanation of the most common cognitive errors in clinical reasoning. Finally, an overview of clinical decision support systems is provided in chapter 5.1. This way, the reader can easily navigate between the topics to understand the key findings. Derived from the results, a theoretical framework on how CDSS might improve the diagnostic process of junior doctors in emergency departments is elaborated in chapter 5.2, serving as the discussion of this thesis. This modified structure facilitates comprehension and enhances readability throughout the thesis while maintaining a logical organization.

3 Dual-process Theory

The psychology of human reasoning gained significant attention in the second half of the last century, questioning the assumption that adults reason according to logic. Studies from this time discovered various systematic errors in human decision-making, challenging the presumed rationality. However, this view of biased and illogical human reasoning seemed paradoxical when considering the achievements of human beings. Additionally, other studies found that adults in fact do act rationally. From these controversial findings, that humans can act both rationally and illogical, a new field in psychology emerged trying to resolve this paradox. The proliferation of numerous *dual-process theories (*DPTs) has resulted in an extensive and at times opaque body of literature (Barrouillet, 2011, pp. 79–80). Authors (J. Evans & Frankish, 2009; Kahneman, 2011) have made concerted efforts to synthesize and summarize these findings in order to bring clarity and coherence to the field. Despite all their differences, some key similarities unite the dual-process theories. They assume that 2 types of mental processing exist, also referred to as *system 1* and *system 2*. The first type, system 1, often seen as evolutionarily primitive, is unconscious, fast, automatic, highly contextualized, and largely independent of working memory resources and general intelligence. The second type, system 2, is deliberative, conscious, controlled, slow, and demanding of working memory resources, underpinning analytical, logical reasoning and normative responses (Barrouillet, 2011, p. 80).

Dual-process theory suggests that these 2 systems are qualitatively different and coexist in adults, competing for controlling behaviour. This new perspective on human reasoning had a significant impact on the way other disciplines approach decision-making, including medicine. Although debate whether DPT is the right model to explain human decision-making is ongoing (J. St. B. T. Evans & Stanovich, 2013, p. 223; Grayot, 2020, p. 106), dual-process theory is commonly accepted as the framework for clinical reasoning, where it is used to investigate decision-making processes of clinicians (Adams et al., 2017, p. 70; Raharjanti et al., 2021, p. 3). To gain a deeper understanding of the two systems posited by dual-process theory, an explanation of system 1 and system 2, based on the Nobel laureate Daniel

Kahneman’s seminal work “Thinking, fast and slow”, will be undertaken in the following chapter.

3.1 System 1 and system 2

System 1, according to dual-process theory, is one of the two cognitive systems that govern decision-making in humans. System 1 is characterized by its *fast, automatic, intuitive,* and emotional nature. It operates with *minimal conscious effort* and often outside of our awareness. Due to its involuntary nature, system 1 cannot be directly controlled. System 1 is responsible for many of the mental processes that happen automatically including simple calculations, recognizing familiar objects or faces, understanding simple sentences, and making snap judgments based on intuition or prior experiences (Kahneman, 2011, pp. 20–28).

A key concept of system 1 is *associative activation*, which involves the automatic triggering of related concepts or memories when a stimulus is encountered. The triggered ideas are interconnected, resulting in a self-strengthening network of associated ideas that shape our perception and understanding of the world. Associative activation can lead to the *priming effect*, wherein exposure to a stimulus influences the response to a subsequent, related stimulus (Kahneman, 2011, pp. 50–54). A compelling example of associative activation and the priming effect is the "Florida effect" (Kahneman, 2011, pp. 50–53). In this study, participants were asked to rearrange scrambled sentences containing words associated with old age, such as "Florida," "forgetful," "bald," "grey," and "wrinkle." After completing the task, the participants walked more slowly to another room compared to a reference group that was not primed with words related to old age. When questioned afterwards, the participants revealed that the idea of old age had not even come to their conscious awareness. Nevertheless, their behaviour had changed. This unconscious change in behaviour emphasizes the power of associative activation and the priming effect, and demonstrates how such mental processes can influence thoughts, feelings, and behaviours without conscious awareness.

The basic cognitive functions of system 1 require hardly any effort, which is why multitasking simple tasks is possible. System 1 serves as our *default cognitive mode*, enabling us to perform routine tasks efficiently and conserving cognitive resources for more demanding activities (Kahneman, 2011, pp. 20–28). It is also our fallback system in case of emergency. It then assigns total priority to self-protection actions (Kahneman, 2011, p. 35).

In contrast to system 1, system 2 is the *slow, deliberate, and analytical* part of the brain. It is responsible for conscious thought, complex problem-solving, and activities that require a high degree of mental effort. There is a wide range of examples for system 2 processes, such as counting the occurrences of the letter "a" one the page of a book, concentrating on the voice of a particular person in a noisy room or solving a complex math problem. System 2 possesses the capability to follow rules, compare different objects regarding their attributes and make deliberate choices between options. Performing these tasks is *effortful* (Kahneman, 2011, pp. 20–24, 36).

As per Kahneman, the *law of least effort* suggests that humans engage system 2 only, when necessary, given that system 1 operates more energy-efficiently. Therefore, the default system humans use is system 1. There is, however, a state of mind, when performing cognitive demanding tasks is not aversive, but rather enjoyable. This "flow" state can be described as effortless, deep concentration and can be induced by many different activities, depending on the individual (Kahneman, 2011, pp. 33–40).

Cognitive Load Theory provides valuable insights into the allocation of mental resources. It suggests that individuals utilize different parts of their memory, namely sensory memory, long-term memory, and working memory. Sensory memory and long-term memory store information for later recall, while working memory is used to manipulate stored and new information. Unlike sensory and long-term memory, *working memory has limited capacity*. When the amount of information in working memory, known as *cognitive load*, exceeds its capacity, *cognitive overload* can occur. Cognitive load can be divided into three categories: intrinsic load, extrinsic load, and germane load. Intrinsic load refers to the cognitive demands essential to a task itself, while extrinsic load consists of non-essential information. Germane load involves information that will be stored as part of a framework for future long-term memory (Harris & Santhosh, 2022, p. 29).

As a result of the limited capacity in working memory, attention must be strategically allocated to focus on the most critical task at hand. When mental effort is high, physical signs like dilated pupils and an increase in heart can be detected. However, the required mental effort for performing a specific task may change over time. As an individual gains experience and becomes more skilled at a task, the energy demand for that task decreases (Kahneman, 2011, pp. 33–40).

System 2 comes to conclusion by effortfully direction attention and searching memory for answers when required. System 1, by contrast, is continuously engaged in monitoring both internal and external stimuli, and it performs *basic assessments* that serve as the foundation for our intuitive judgments. These basic assessments are considered to be evolutionarily crucial, as they have been fundamental to humankinds' survival by serving as early warning signals of potential danger. These basic assessments of system 1 still play an important role in the process of arriving at conclusions (Kahneman, 2011, pp. 89–96)

System 1 is responsible for monitoring internal and external stimuli and making preliminary decisions based on these assessments. These decisions, however, are not final. They serve as suggestions for system 2, which subsequently evaluates their validity (J. St. B. T. Evans, 2019, p. 1). This evaluation process demands cognitive resources, and, as a result, is only employed when system 1's judgment appears erroneous or when individuals actively engage system 2. In other words, since the brain is generally conservative in its allocation of effort towards the energy-intensive system 2, it often decides to trust the intuitive judgments of system 1, unless there is a compelling reason to intervene (Kahneman, 2011, pp. 44, 45).

Further aggravating the matter is the fact that the assessment, whether extra effort by system 2 is needed, is typically a decision made by system 1. The indicator used for this decision is how easy the respective answer to the problem came to mind. This measure is called *cognitive ease* which can range from easy to strained. However, the ease with which something comes to mind is not necessarily a reliable indicator of its accuracy or truthfulness and can lead to overconfidence in decisions (Kahneman, 2011, pp. 45, 59–62).

The following chapter aims to provide an overview of the limitations of the suggestions made by system 1. Specifically, it discusses how the heuristic and automatic nature of system 1 may result in cognitive biases and less-than-perfect assessments.

3.2 Heuristics and Biases

Heuristics are mental shortcuts or simplified strategies that the brain employs, particularly in system 1, to make complex cognitive tasks more manageable. They are automatically and unconsciously employed and can facilitate decision-making. However, heuristics are not without their drawbacks, as they can often lead to errors, so called *cognitive biases* (Committee on Diagnostic Error in Health Care et al., 2015, pp. 55, 56; Kahneman, 2011, pp. 98, 99). In the subsequent chapters, important heuristics with their cognitive biases will be discussed.

3.2.1 Substituting hard questions

There are various ways, how system 1 uses heuristics for facilitating decision-making.

One common cognitive strategy employed by system 1, and seen in almost all heuristics, is the substitution of hard questions with easier ones. It allows individuals to quickly generate responses to complex questions, even when they might lack the relevant knowledge or experience to accurately address the original question. However, such mental shortcuts can lead to systematic errors and overconfidence in judgments based on the simplified, substituted question (Kahneman, 2011, pp. 98, 99).

Cognitive ease, as discussed in the last chapter, is an indicator for how easy something comes to mind. This indicator is then used by system 1 to assess the validity of the answer. When the answer comes to mind with cognitive ease, it is more likely to be accepted as true or valid. Cognitive ease itself is an example for a mental shortcut, system 1 uses, to answer a hard question, “How correct is the answer I suggested?”, by replacing it with an easy one, “How easy did this information come to mind?” (Kahneman, 2011, pp. 59–62).

3.2.2 Availability

The *availability heuristic* is defined as the process of judging frequencies based on the ease with which instances come to mind. When asked a question, for example how many different dog breeds there are, system 1 will look for known instances, like “Golden Retriever” or “Poodle”, within that class. Depending on how many instances come to mind, and more importantly, with how much ease this happens, the estimations differ. The availability heuristic allows system 1 to make rapid judgments about the likelihood of events or the frequency of occurrences. Again, a hard question, “How many dog breeds are there?”, is replaced by an easy one, “With how much cognitive ease do dog breeds come to mind?” (Kahneman, 2011, pp. 129, 130).

The availability of information is significantly influenced by various factors. Salient or dramatic events, as well as personal experiences, vivid images, and striking examples can be retrieved from memory with ease (Kahneman, 2011, pp. 130, 131). Also, the emotional response induced by associative activation can strongly influence the ease with which certain information come to mind (Kahneman, 2011, pp. 138, 139). Media coverage of plane crashes, which are inherently dramatic and emotionally charged, for example, can lead individuals to overestimate the likelihood of such events occurring. This overestimation can result in a systematic cognitive error called *availability bias*.

Availability bias occurs when individuals make judgments or assessments based on the ease with which relevant examples come to mind, rather than considering all relevant data, leading to cognitive distortions and skewed perceptions of reality. This can ultimately result in erroneous decisions while being overconfident in one’s judgements (Kahneman, 2011, pp. 130, 131).

3.2.3 Confirmation

When individuals are confronted with a statement, for example “Horses can fly.”, system 1 initially attempts to comprehend and accept the statement as true. In other words, to understand the statement, humans must first imagine what it would mean if the statement was true (Kahneman, 2011, pp. 80, 81). Only then system 2 can intervene and challenge the assumption made by system 1 (Kahneman, 2011, p. 44). This way of thinking has a significant flaw: if system 2 is otherwise engaged or sufficient mental resources are not available, humans may accept false statements as true. This cognitive process can contribute to *confirmation bias*, the mind's natural tendency to favour uncritical acceptance of suggestions. System 1's automatic and associative nature predisposes it to accept information without questioning it’s validity (Kahneman, 2011, p. 80,81).

3.2.4 Anchoring

The anchoring heuristic is defined as the process of making estimates or decisions based on an initial reference point or "anchor" that has an undue influence on the subsequent judgments. This process occurs subconsciously, and our conscious mind often has no control over or awareness of its impact. This explains why even arbitrary numbers, unrelated to the actual value, can still influence an individual's judgment (Kahneman, 2011, pp. 119, 120, 127).

Anchoring can affect both system 1 and system 2 thinking. In system 1, the anchor serves as a primer, influencing the information that comes to mind with cognitive ease. In system 2, the anchor acts as a reference point from which it attempts to adjust towards a more accurate answer. However, especially when system 2 is fatigued, this adjustment is often insufficient, resulting in *anchoring bias*. Anchoring bias occurs when individuals make judgments or assessments that are disproportionately influenced by the anchor, rather than considering all relevant data. For example, when negotiating the price of a car, the initial asking price presented by the seller can serve as an anchor, causing the buyer to make counteroffers around that figure, even if the car's actual value is significantly different. Anchoring bias can also lead to cognitive distortions and ultimately erroneous decisions (Kahneman, 2011, pp. 120–123).

3.2.5 Representativeness

Representativeness is a cognitive heuristic, or mental shortcut, that people use to judge the likelihood of an event based on how similar it is to a prototypical representation or stereotype. The hard question of a probability gets replaced by the easier question of plausibility. In other words, instead of trying to calculate actual probabilities, which can be quite complex, this cognitive heuristic focuses on how similar the situation is to a known example. This heuristic can be helpful in various contexts, such as making rapid assessments or forming impressions in social situations (Kahneman, 2011, pp. 148–151).

However, the representativeness heuristic can also lead to errors and biases in judgment. One common bias that results from the use of representativeness is *base rate neglect*. This occurs when individuals ignore the overall frequency or prevalence of an event or category in favour of the specific features of the case at hand. In other words, the decision-making process is influenced more by the perceived similarity between the information presented and a familiar stereotype than by an actual evaluation of probabilities (Kahneman, 2011, pp. 148–151).

Bayes' theorem is a statistical concept that can help individuals to make more accurate judgments. This concept prompts individuals to consider base rates initially and only then update those rates with additional information. For example, when assessing the likelihood of a person with a strong interest in computers being a computer scientist, the best approach would be to first consider the likelihood of any person being a computer scientist. This is the base rate. Only then, the additional information, that the person is computer-affine, should be considered by comparing the proportion of computer scientists being highly interested in computer with the proportion of non-computer scientist with the same interests. This judgement on representativeness should then be considered to update the prior judgement on the base rates. By doing so, the estimations are closer to the base rates, ultimately leading to better judgements (Kahneman, 2011, pp. 153, 154, 461).

3.3 Being an Expert

The intuitive suggestions of system 1, also referred to as “gut feeling” by some authors (Pelaccia et al., 2011, p. 2), are a key component in everyday decision-making. The process of decision-making involves the interplay between system 1, generating suggestions, and system 2, checking the validity of those suggestions (Kahneman, 2011, pp. 235–237). As discussed in the chapters on biases, the suggestions of system 1 are often misleading or wrong. There are, however, situation, where intuition can be trained and therefore usually be trusted. The development of valid intuition occurs when individuals have learned to recognize familiar patterns in new situations (Kahneman, 2011, p. 12).

The study of experts' intuitions has been approached by two main groups of researchers. On one hand, the heuristics and biases approach examines human reasoning critically, frequently highlighting the unreliability, susceptibility to error, and inconstancy of cognitive processes, particularly those that origin within the intuitive system 1. On the other hand, the naturalistic decision-making approach aims to unravel the mystery of expert reasoning. Researchers in this field seek to understand the strategies and data employed by the human brain when making rapid and effective decisions in complex, real-world environments (Pelaccia et al., 2020, p. 206). While Kahneman’s ideas primarily align with the heuristics and biases approach, he acknowledges the value of the naturalistic decision-making approach. He emphasizes that understanding the strengths and weaknesses of both perspectives can lead to a more comprehensive understanding of expert intuition and decision-making (Kahneman, 2011, pp. 234, 235).

Although the two schools have a different view on experts intuition, Kahneman reached consensus with one of the main proponents of the naturalistic decision-making approach, Gary Klein: To nurture accurate and reliable intuition, it is essential that two basic conditions are met (Kahneman, 2011, pp. 234–240):

1. The environment must be sufficiently regular to be predictable.
2. System 1 must have the opportunity to learn these regularities through prolonged practice.

When both these conditions are fulfilled, intuitions are more likely to be skilful and trustworthy. For example, expert chess players can quickly identify strong moves in a given position, thanks to their extensive experience and practice in a structured environment. However, in situations where stable regularities in the environment are absent, or when individuals haven’t had the opportunity for prolonged practice, intuitions can be misleading (Kahneman, 2011, p. 241).

3.4 Summary of dual-process theory

Dual-process theory is a framework that seeks to explain human decision-making through the interaction of two distinct systems. System 1 thinking is fast, intuitive, automatic, and highly energy-efficient, making it the default mode of thinking for continuously monitoring internal and external stimuli. In contrast, System 2 thinking is slow, deliberate, and analytical, requiring significant amounts of energy and thus reserved for situations where it is necessary. System 2 is responsible for evaluating system 1's suggestions and, when detecting errors, correcting them. System 1 employs mental shortcuts, also called heuristics, to simplify decision-making. These heuristics often involve substituting a complex question with a simpler one, enabling system 1 to generate a quick response. While these shortcuts are generally helpful, they can sometimes fail and result in cognitive errors, also known as biases. These biases are systematic deviations from logical, statistical, or rational judgment, and can significantly impact the quality of decisions made by individuals in various contexts. It is, however, possible to train system 1 to make effective decisions in an energy-efficient manner. Key prerequisites for successful system 1 training include a stable and predictable environment and sufficient time for the individual to discern the regularities of this environment.

4 Clinical Reasoning

In the field of medicine, the cognitive processes underlying decision-making are referred to as *clinical reasoning*. The literature uses various terms to describe clinical reasoning, such as "critical thinking," "problem-solving," "diagnostic reasoning," and "decision-making" (Pelaccia et al., 2020, pp. 206, 207). Some authors use these terms interchangeably, others differentiate between them (Pelaccia et al., 2020, p. 206). For this thesis, clinical reasoning is seen as a critical skill for clinicians and refers to the cognitive processes involved in clinical practice that encompass thinking and decision-making. It involves synthesizing various clinical and investigative data to generate and prioritize differential diagnoses and develop targeted treatment plans and is therefore key to effectively manage patients (Croskerry, 2009a, p. 1022; Linn et al., 2012, p. 1; Thampy et al., 2019, p. 1631). It is the process of knowing and doing in patient care (Raharjanti et al., 2021, pp. 1–2). Since clinical reasoning is omnipresent in patients care, it is seen as a major determining factor of clinical competence (Pelaccia et al., 2011, p. 1).

Dual-process theory has risen to the prevailing framework of clinical reasoning (Adams et al., 2017, p. 70; Croskerry, 2009b, p. 33), since it incorporates other extensively described theories within the medical literature, like pattern recognition, illness script theory and hypothetico-deductive reasoning (Pelaccia et al., 2011, p. 2; Raharjanti et al., 2021, pp. 1–4; Thampy et al., 2019, pp. 1631, 1632). Clinical reasoning is currently regarded as a universal model of reasoning, both in general literature as well as in literature specific to clinical reasoning (Pelaccia et al., 2011, p. 207). In the subsequent sections, dual-process theory as it relates to clinical reasoning will be discussed, while also offering a brief overview of pattern recognition, illness script theory and hypothetico-deductive reasoning. Following that, the particularities of clinical reasoning among junior doctors will be examined and the unique aspects of clinical reasoning within emergency departments will be explored. Finally, the most common sources of errors in clinical reasoning will be analysed.

4.1 Clinical reasoning theories

4.1.1 Pattern recognition and script theory

System 1 can recognize typical patterns (Pelaccia et al., 2011, p. 2). This property is often described in medical literature as *pattern recognition* or *illness script theory* (Croskerry, 2009a, p. 1023, 2009b, p. 30; Durning et al., 2015, p. 169; Marcum, 2012, p. 956; Pelaccia et al., 2011, p. 3; Raharjanti et al., 2021, p. 3; Thampy et al., 2019, p. 1631).

Pattern recognition is a crucial aspect of clinical reasoning and is the most common form of non-analytical processing. It involves unconsciously linking a given clinical situation with patterns stored in long-term memory, allowing clinicians to quickly generate diagnostic hypotheses when encountering a patient for the first time. This fast, automated cognitive operation relies on the identification and processing of clinical and contextual information based on past experiences and is widely used by clinicians, regardless of their expertise (L. N. Medford-Davis et al., 2018, p. 1099; Pelaccia et al., 2011, p. 3).

Pattern recognition is strongly related to system 1 thinking. It is characterized by heuristics, mental shortcuts, and intuitive processes that engage automatically and unconsciously when salient features of a clinical presentation are recognized. This enables physicians to rapidly and effortlessly diagnose conditions based on their characteristic appearance by retrieving the most appropriate exemplar for the case at hand from memory. For instance, the majority of doctors can easily identify the distinctive pattern and manifestation of herpes zoster, as well as the combination of signs and symptoms related to an acute myocardial infarction. Pattern recognition is, in other words, the formulation of an initial hypothesis about a disease by matching the current clinical case with a similar previous experienced one (Croskerry, 2009a, p. 1023; Durning et al., 2015, p. 169; Marcum, 2012, p. 956).

System 1 thinking, driven by pattern recognition, is fast, effortless, and often results in accurate diagnoses (Croskerry, 2009a, p. 1023, 2009b, p. 30). However, it is prone to failure when encountering atypical or overlapping presentations, leading to diagnostic errors (Croskerry, 2009b, p. 31). Despite its limitations, pattern recognition performed automatically by system 1 thinking plays a critical role in clinical reasoning, as it is rare in clinical practice to have access to all necessary information needed for making well-informed decisions and system 1 is capable of managing this uncertainty (Croskerry, 2009a, p. 1022).

Expanding on the idea of pattern recognition within system 1 thinking, illness script theory provides a deeper understanding of how clinicians automatically try to match symptoms of a given clinical situation to a known pattern stored in memory. Illness script theory is a knowledge organisation model (Audétat et al., 2017, p. 793) suggesting that illness scripts are the clinicians expected representation of a disease. These scripts guide clinicians in diagnosing patients and can be activated unconsciously through pattern recognition. When a patient is encountered, the initial information triggers one or more relevant illness scripts. These scripts not only predict the sequence of events but also guide the clinician's approach to the case. As more patient information is gathered, those scripts that align with the patient's characteristics are strengthened, while those that are less relevant are weakened or disregarded. The most probable diagnosis corresponds to the script that shares the most similarities with the patient. This process is similar to the concept of representativeness matching from chapter 3.2.5 (Raharjanti et al., 2021, p. 3; Thampy et al., 2019, p. 1631).

Illness script theory can be linked to dual-process theory. The initial comparison between the presentation of the patient with the memorized illness scripts is a system 1 operation. If this initial comparison proves to be inconclusive, for example when clinicians face cases where no discernible pattern or script is immediately available, a more careful and deliberate reasoning process is required with system 2 becoming engaged. This type of processing relies on a more rational reasoning approach. To determine the most probable diagnosis, diagnostic hypotheses are analytically examined. This approach is often referred to as the hypothetico-deductive model (Raharjanti et al., 2021, p. 3; Thampy et al., 2019, p. 1631).

4.1.2 Hypothetico-deductive reasoning

The hypothetico-deductive model was an early attempt to describe the clinical reasoning process, where clinicians generate diagnostic hypotheses and test their logical consequences through further investigations. This process ultimately leads to a diagnostic decision (Raharjanti et al., 2021, pp. 2, 3). The hypothetico-deductive model emerged from the Medical Inquiry Project in the early 1970s, and it involves generating a limited number of hypotheses and gathering additional clinical evidence until a final diagnosis is made (Marcum, 2012, pp. 956, 957). It is therefore a process in which diagnostic hypotheses are tested analytically, and considered to be a common form of clinical reasoning (Pelaccia et al., 2011, p. 3). In the context of the dual-process theory, hypothetico-deductive clinical reasoning corresponds to the analytical, slow system 2 thinking (Pelaccia et al., 2011, p. 3). System 2 thinking is prompted when the intuitive system 1 is unable to generate relevant solutions to complex or rare problems (Pelaccia et al., 2011, p. 3). Although, the hypothetico-deductive model has been highly influential in shaping our understanding of clinical reasoning, today it is recognized as only a part of the clinical reasoning process and not an all-inclusive theory, as it is integrated with other cognitive processes (Marcum, 2012, pp. 956, 957).

In daily practice, clinical reasoning involves both system 1 and system 2 processing. The combination of strategies is thought to be superior compared to using either strategy alone. As clinicians obtain initial patient data, including symptoms, clinical signs, and relevant patient characteristics, system 1 processing is immediately and subconsciously activated. Should a representative pattern that matches the case at hand be found, it will form the foundation for the diagnostic decision. However, if pattern recognition fails to take place for any reason, system 2 processing will be initiated to organise and make sense of the information. In addition, system 2 analytic processing is engaged to either confirm or refute the diagnostic hypotheses generated by system 1 (Durning et al., 2015, p. 174; Harris & Santhosh, 2022, p. 28; Raharjanti et al., 2021, pp. 2, 3).

4.2 Clinical reasoning among junior doctors in the emergency department

Clinical reasoning, the process through which healthcare professionals make decisions based on available information, is a vital skill for all physicians. To evaluate clinical reasoning among junior doctors in emergency departments, a framework proposed by Adams et al. will first be discussed. Then the specifics of emergency departments will be elaborated. Finally, the critical differences in the decision-making process between an experienced physician versus a junior doctor will be explored.

4.2.1 Framework of junior doctors clinical reasoning in EDs

Clinical reasoning of junior doctors in emergency departments is a complex process. It involves the combination of system 1 and system 2 thinking, which are in constant dialect with each other (Adams et al., 2017, p. 70). According to Adams et al., the decision-making process can be divided into three main phases: case framing, evolving clinical reasoning, and management of ongoing uncertainty.

The first stage of clinical reasoning for junior doctors in emergency departments is called case framing, which determines the urgency of approach for a patient. This process involves two notions: initial cues and first impressions.

Initial cues are background clinical information that helps doctors mentally prepare for the case. They include out-of-hospital written assessments, within-hospital written assessments, assessments from prior admissions, social cues, and upfront data results (Adams et al., 2017, p. 72). In cases of extreme uncertainty or when laboratory tests have already returned from the waiting room before the first evaluation, hypotheses may be generated bottom-up based on data instead of top-down based on symptoms. Initial cues can therefore have a major impact on the decision-making process of physicians, as they can act as anchors (Kahneman, 2011, p. 120; L. N. Medford-Davis et al., 2018, p. 1099). Initial cues can influence a doctor's level of caution, depending on factors such as the patient's triage department or the doctor's familiarity with a specialty area. Some junior doctors developed strategies to minimize risk of bias from initial cues.

First impressions involve a rapid assessment of a patient's acuity based on their overall appearance, often referred to as the "eyeball test" or "end-of-bed-o-gram." Although these intuitive judgments are informed by prior experience and reflective analysis, doctors are able to verbalize key descriptors of their assessments, indicating a system 2 involvement (Adams et al., 2017, p. 72).

The second stage of clinical reasoning for junior doctors in emergency departments is called evolving clinical reasoning, which aims to pinpoint the diagnosis and decide on admission. This stage involves two broad categories: instant recognition, which is system 1 dominant, and the system 2 dominated non-recognition.

Instant recognition includes single cue and pattern recognition, where doctors identify a primary diagnosis from a single critical cue or a classic combination of symptoms and signs. Checkpoint strategies, such as using red flags and rule-out of dangerous mimics, help minimize errors in instant recognitions. Reflective diagnostic time-outs are also used to review initial assessments, but time pressure can discourage this practice, leading to potential errors.

Non-recognition of the case involves hypothetico-deductive reasoning, where doctors construct a list of possible diagnoses, subsequently eliminating many of them using history, examination, and investigations. Junior doctors use rehearsed question sets and a strategy called "chunking" to manage multiple symptoms. They also employ an iterative approach, using longitudinal observation to test and confirm diagnostic hypotheses before making discharge decisions. Iterative reasoning incorporates longitudinal impressions, social cues, and new clinical information. However, excessive double-checking can also occur in this stage (Adams et al., 2017, pp. 72, 73).

The third stage of clinical reasoning for junior doctors in emergency units involves managing ongoing uncertainty, where they address diagnostic uncertainty and anxiety. To handle this uncertainty, junior doctors employ specific mitigating strategies.

One strategy is expanding the clinical encounter, in which doctors delay discharge decisions up to the maximum allowed time or use decision units for ongoing tests and treatment. They also follow up on patients during the next shift to reduce residual uncertainty and learn from it.

Another strategy involves concrete decision-making, where doctors simplify and precipitate discharge decisions by considering the worst possible consequence of sending the patient home or using clinical prediction rules to guide decisions. Ultimately, if doctors have ongoing concerns, the decision is based on whether the patient is considered unwell, in which case admission is required.

Lastly, junior doctors share responsibility for decision-making by discussing discharge decisions with consultants, peers, and even patients. Informal sharing of thoughts and decision-making with colleagues is common, as it provides reassurance and support. Safety netting, which involves giving specific advice to patients about what constitutes a worrying deterioration, is also used to share responsibility with patients (Adams et al., 2017, pp. 73, 74).

In conclusion, the decision-making process in junior doctors working in emergency departments is a complex interplay of intuitive and analytical cognitive processes, influenced by factors such as prior knowledge, experience, time pressure, and ongoing uncertainty. Although there are some limitations to the study of Adams et al., like retrospective recall of cases and a narrow geographical remit, their model offers valuable insights into the clinical reasoning process of junior doctors in emergency departments. Their findings align with the clinical reasoning theories discussed in chapter 4.1. Moreover, the results of Adams et al. underscore the engagement of both systems. While initial intuition is primarily a system 1 operation, the system 2 dependent hypothetico-deductive reasoning also plays an important role in the clinical reasoning process, particularly when system 1's suggestions do not produce a satisfactory outcome.

4.2.2 Specifics of emergency departments

This chapter will discuss the distinct aspects of emergency departments that can substantially affect the decision-making process of physicians, mainly by increasing cognitive load. The demanding environment of emergency departments calls for fast decision-making, often only with access to limited information. Furthermore, physicians are required to proficiently manage multiple patients concurrently, while facing interruptions and a high level of uncertainty (Pelaccia et al., 2020, p. 207). Factors influence clinical decision-making in emergency units can be divided into 3 main groups: contextual, patient and physician factors.

First, several contextual factors have been identified that influence clinical reasoning in the emergency department (Pelaccia et al., 2020, p. 211). The environment is less structured compared to other specialties, with physicians under pressure to rapidly diagnose, treat, and provide disposition for a high volume of patients arriving

at irregular times throughout the day with an unpredictable variety of illnesses and acuities. An ED shift requires hundreds of decisions both about patient treatment and about prioritization of multiple competing patients and tasks. While trying to make these decisions, providers are interrupted every 3 to 6 minutes, leaving them with only a short amount of time available to collect the necessary history to make a diagnosis (Medford-Davis et al., 2018, p. 1098). All these factors put a strain on working memory capacity (Harris & Santhosh, 2022, p. 29). Time pressure in the ED is another significant constraint, which may lead to physicians cutting corners in the assessment process to avoid delays, resulting in incomplete collection of initial cues and premature initiation of management steps before fully discussing the case with the patient (Adams et al., 2017, p. 73). This time pressure can explain why, if a physician is reasonably certain about the list of potential diagnoses, they typically stop asking questions regardless of whether they have obtained all relevant information (L. N. Medford-Davis et al., 2018, p. 1099).
Interruptions can further increase cognitive load of physicians in emergency departments (Harris & Santhosh, 2022, p. 29; Pelaccia et al., 2020, p. 211). In addition to interruptions, fatigue, uncertainty, and stress, all common in the ED, can also cause people to default back to the fast type of system 1 thinking (L. N. Medford-Davis et al., 2018, p. 1101). Not only is system 1 thinking more susceptible to cognitive errors, Preisz has suggested that intuitive reasoning might undermine the slow, deliberative thought required for ethical reasoning and decision-making, potentially leading to long-term burdens on patients and their families (Preisz, 2019, pp. 621–624)

Second, there are several factors regarding the patient that can influence clinical reasoning in emergency departments. While factors like gender and ethnicity have only yielded weak or inconsistent results (Pelaccia et al., 2020, p. 211), difficulties in communication have been shown to complicate the clinical reasoning process. Communication problems can arise due to hearing deficits, language or cultural differences or due to the emotional or physical distress encountered by patients in emergency units. These difficulties in communication complicate history taking, reduce physicians' confidence in the accuracy of the data, and increase diagnostic uncertainty (L. N. Medford-Davis et al., 2018, p. 1098; Pelaccia et al., 2020, p. 211).

Finally, physician factors, including specialized training, experience, mood, confidence, gender, and risk aversion can influence clinical reasoning in emergency departments. However, many of these findings have produced inconsistent results, with the exception of experience, mood and confidence, which have been shown to influence the clinical reasoning process (Harris & Santhosh, 2022, p. 30; Pelaccia et al., 2020, pp. 211, 212).

In conclusion, the unique environment of emergency departments significantly affects the clinical reasoning of physicians working there. Factors such as time pressure, frequent interruptions, and a high degree of uncertainty greatly influence the cognitive processes involved in decision-making. Additionally, various contextual, patient, and physician factors add to the complexity of clinical reasoning in emergency departments. These unique challenges often lead to an increased cognitive load, causing physicians to depend more on the quick, intuitive system 1 thinking in their decision-making processes. In the following chapter, the consequences of this situation will be elaborated.

4.2.3 Differences between junior doctors and experienced physicians

As discussed in the previous chapters, clinical reasoning in emergency departments hinges on the physicians ability to recognise patterns of symptoms and to match these patterns to known diseases in order to come to a diagnosis. This process, however, heavily relies on the amount and distinctiveness of patterns, or illness scripts, the physician has been able to store in long-term memory. As explained in chapter 3.3, the opportunity to learn typical patterns of diseases through prolonged practice is a basic requirement for acquiring skill (Kahneman, 2011, p. 240). Since junior doctors hardly had the opportunity to learn such patterns, they appear unprepared for clinical reasoning and emergency management (Monrouxe et al., 2017, p. 1). Becoming an expert is a matter of accumulating a comprehensive set of robust prototypes and readily recallable experiences, as well as developing a range of adaptable strategies for problem-solving (Croskerry, 2009a, p. 1023; Durning et al., 2015, p. 169).

Unlike junior doctors, experts have accumulated a wide range of illness scripts they can use to make sense of a new situation (Raharjanti et al., 2021, p. 3). Comparing

a current case with illness scripts stored in long-term memory is a system 1 operation, and checking for representativeness is a straightforward, intuitive, and energy-efficient method for diagnosing patients. Therefore, although self-reporting to use more analytical reasoning, many studies showed that experts tend to use more intuitive processes compared to junior doctors (Cleland et al., 2021, p. 2; Marcum, 2012, p. 956; Pelaccia et al., 2020, p. 210).
Although experts tend to rely on intuitive reasoning, intuitive and analytical reasoning are in constant dialect (Adams et al., 2017, p. 71). System 2 thinking, is used for atypical cases or at life-threatening situations, for example (Pelaccia et al., 2020, p. 210).
Findings from the literature review suggest, that although junior doctors can also reach diagnostic accuracy, the process of doing so is fundamentally different and less energy efficient compared to their experienced colleagues. A problem easily solvable by an expert could necessitate significant system 2 engagement for a junior doctor, resulting in increased cognitive load (Cleland et al., 2021, p. 6; Durning et al., 2015, p. 174).

An illustrative example of the differences in reasoning processes, as demonstrated by Cleland et al., reveals that junior doctors, who rely more on system 2 thinking, are more susceptible to the effects of sleep deprivation. This is because sleep deprivation primarily impairs system 2, while system 1 remains relatively unaffected, giving experienced physicians an advantage in such conditions (Cleland et al., 2021, pp. 1–6). These findings, however, stand in contrast to the result of Durning et al., which suggest, that fatigue leads to an impairment of the non-analytical system 1. The study of Durning et al. should, however, be considered cautiously, since, as they discuss in the limitations of their study, the sample size was very small (Durning et al., 2015, p. 174).

In conclusion, the primary differences between junior doctors and experienced physicians regarding clinical reasoning lie in the reliance on intuitive judgments by experts and the dependency on system 2 thinking by junior doctors, resulting in an increased cognitive load for the latter. These disparities become more apparent in challenging conditions such as sleep deprivation. As junior doctors gain experience and accumulate illness scripts, they will progressively develop more efficient, intuitive clinical reasoning capabilities, similar to those exhibited by experienced doctors.

4.3 Errors in clinical reasoning

As discussed in the previous chapters, clinical reasoning is a complex cognitive process involved in many decisions in healthcare. Errors in clinical reasoning, particularly in the diagnostic process, constitute a major challenge in the field of medicine and have significant implications for patient safety (Raharjanti et al., 2021, p. 6). The assessment phase of the diagnostic process was where human errors predominantly occurred. Therefore, the diagnostic process is of utmost importance, as it greatly impacts patient outcomes. These errors may arise from failing to consider the correct diagnosis, giving undue weight to a competing diagnosis, or not recognizing the urgency of the situation (Baartmans et al., 2022, p. 1139). In fact, a study conducted in Japan revealed that 68.5% of error cases were attributed to errors in the diagnostic process (Miyagami et al., 2023, p. 342). In this chapter, we will explore the various factors and circumstances that contribute to errors in clinical reasoning, with a particular focus on the challenges faced by junior doctors in emergency departments.

Although numerous methods have been proposed by authors to explain errors in clinical reasoning, this thesis will focus on presenting a framework that incorporates dual-process theory. DPT, as discussed in the chapters above, suggests that system 1 tries to make sense of a given situation by looking for representative cases stored in long-term memory. If this process is inconclusive or obviously erroneous, system 2 will be consulted. Based on this theory, several points where the diagnostic process might fail, can be derived: First, System 1 fails to provide the right diagnosis, second, system 2 fails to recognise the error and third, system 2 cannot correct the error due to the lack of knowledge.

4.3.1 Failure in System 1

One of the primary reasons, system 1 can fail, is the misinterpretation of a given clinical situation. The accuracy of pattern recognition largely relies on the clinician's previous experience with the condition, as well as the representativeness of a case, meaning its pathogenicity (Croskerry, 2009b, p. 31). System 1 is especially prone to fail when confronted with a highly atypical representation of a disease (Raharjanti et al., 2021, p. 3). Additionally, factors like the lack of access to information about the patient negatively influences system 1’s abilities (Raharjanti et al., 2021, p. 6). Therefore, system 1’s suggestions will be influenced by the information available, the automatic processing of these information, as well as the amount and clarity of representative patterns, or illness scripts, stored in long-term memory (Croskerry, 2009b, p. 31; L. N. Medford-Davis et al., 2018, p. 1099). An alternative perspective is the proposition that the lack of information and representative illness scripts can lead to flawed heuristics, resulting in cognitive biases. Cognitive biases have been studied by various authors (Audétat et al., 2017; Coen et al., 2022; Committee on Diagnostic Error in Health Care et al., 2015; Croskerry, 2009a, 2017; L. N. Medford-Davis et al., 2018; Norman et al., 2017; Preisz, 2019; Raharjanti et al., 2021; Thampy et al., 2019). Coen et al. conducted an analysis of the most common cognitive biases in the context of the COVID-19 pandemic. The environment found in the COVID-19 pandemic was characterised by a high level of stress and uncertainty. These conditions are similar to those often experienced in emergency departments, where physicians face significant pressure to make rapid decisions while managing a variety of complex cases (Coen et al., 2022, p. 981). Given the similarities between the contexts of COVID-19 patient care and emergency departments, it is reasonable to assume that the findings of Coen et al.'s study may be applicable to emergency department settings. As such, this thesis will discuss the most common biases identified in their study: Cognitive dissonance, premature closure, availability bias, confirmation bias and anchoring bias.

Cognitive dissonance can be defined as the encountered psychological discomfort when holding conflicting thoughts at the same time. In the context of clinical reasoning, cognitive dissonance can arise when the physician’s thoughts about a patient's condition contradict each other, leading to doubts about the accuracy of their diagnosis (Coen et al., 2022, p. 981). Therefore, holding a broad list of conflicting differential diagnoses in memory can lead to cognitive dissonance, a condition the brain tries to avoid.

Premature closure, also known as *search satisficing*, is a cognitive bias in which physicians tend to accept the first plausible diagnosis they encounter without thoroughly exploring alternative possibilities or completing a comprehensive evaluation. An example for premature closure would be a physician in the emergency department that sees a patient who recently developed low back pain and concludes that it is due to lumbar disc disease, without exploring other potential differential diagnoses. This failure of considering reasonable differential diagnoses can lead to diagnostic errors. Adams et al. found that junior doctors are especially prone to premature closure (Adams et al., 2017, p. 74; Coen et al., 2022, p. 981; Committee on Diagnostic Error in Health Care et al., 2015, p. 57; L. N. Medford-Davis et al., 2018, p. 1100).

Availability bias refers to the tendency to perceive a diagnosis as more probable simply because it is easily recalled or comes to mind quickly. For example, if a physician read about a specific diagnosis recently, it will come more easily to mind and will therefore be overestimated (Coen et al., 2022, p. 981; Committee on Diagnostic Error in Health Care et al., 2015, p. 57; L. N. Medford-Davis et al., 2018, p. 1101; Thampy et al., 2019, p. 1632).
Availability bias is not inherently negative, since it can both increase and decrease the accuracy in clinical reasoning (Norman et al., 2017, p. 25).

Confirmation bias in a clinical context occurs when physicians prioritize information that supports their initial diagnostic hypothesis to the point that they ignore evidence that contradicts it (Raharjanti et al., 2021, p. 6). This bias manifests as a tendency to focus on symptoms or signs that validate and interpret clinical findings in a manner that reinforces their initial hypothesis (Coen et al., 2022, p. 981; Thampy et al., 2019, p. 1632). To put it differently, once a diagnosis is formed, physicians tend to view any subsequent evidence that supports it as validation of the diagnosis's correctness, while unconsciously disregarding any evidence that contradicts it (L. N. Medford-Davis et al., 2018, p. 1101).

Anchoring bias suggests that the earliest or most salient features of a patient's history or test results acts as anchors, causing physicians to become attached to a specific diagnostic hypothesis early in the process. This bias can lead to an overreliance on this information and an inability to adjust the diagnosis when new evidence emerges. Initial cues, as discussed in chapter 4.2.1, may act as anchors and therefore influence the decision-making process of physicians (Coen et al., 2022, p. 981; L. N. Medford-Davis et al., 2018, p. 1100; Raharjanti et al., 2021, p. 6; Thampy et al., 2019, p. 1632).

In conclusion, the failure of system 1 in clinical decision-making arises primarily from the misinterpretation of clinical situations, influenced by factors such as the clinician's experience, the representativeness of the case, and the availability of patient information. Atypical disease presentations pose a particular challenge for system 1. Moreover, failed heuristics or cognitive biases can further contribute to the emergence of errors in clinical reasoning.

4.3.2 Failure to detect or correct wrong suggestions

The monitoring and correction of system 1’s suggestions lie in the domain of system 2. It is therefore the mediator between the intuitive suggestions and the final decisions. The ability to check and correct system 1's suggestions is essential for avoiding cognitive errors, but it can be influenced by a variety of factors.

Personal factors that can negatively affect system 2 processing include overconfidence, complacency, and lack of motivation (Raharjanti et al., 2021, p. 6). In addition, inattentiveness, fatigue, and cognitive indolence can all diminish system 2 ability to recognise and correct wrong intuitive suggestions (Croskerry, 2009a, p. 1025).

Contextual factors can also negatively impact the effectiveness of system 2 thinking. Time restrictions, multi-tasking, and distraction are prime examples for such factors. These elements contribute to making the high-stress environments of emergency departments particularly challenging for system 2 thinking (Miyagami et al., 2023, p. 340; Raharjanti et al., 2021, p. 6). For instance, clinicians may face a higher risk of diagnostic error when encountering a case with atypical presentation, for which system 2 thinking is needed, at the end of their shift after an especially exhausting day (Raharjanti et al., 2021, p. 8).

Extreme busyness can lead to cognitive overload and therefore impair system 2's ability to monitor system 1's suggestions (Croskerry, 2009a, p. 1025). Especially in emergency departments, where physicians must rapidly diagnose and treat a high volume of patients with various illnesses, cognitive load can be very high. Physicians in emergency departments also face interruptions every 3 to 6 minutes, leaving limited time for collecting necessary patient history for accurate diagnoses. Additionally, acutely ill patients require urgent intervention, further deferring information gathering and diagnoses for other patients. These constraints can induce cognitive overload, thereby inhibiting system 2's ability to monitor and correct system 1's suggestion, leaving the ED particularly susceptible to diagnostic error (L. N. Medford-Davis et al., 2018, p. 1098). Furthermore, as discussed in chapter 3.1, system 2 thinking requires high amounts of energy and using it often is therefore not aligned with the law of least effort (Kahneman, 2011, p. 35). This principle suggests that humans inherently tend towards those thinking processes that require less energy. This preference can be attributed to the "cognitive miser function", which Croskerry explains as a natural predisposition of the brain to minimize effort and seek cognitive ease (Croskerry, 2017, p. 10).

In summary, personal and contextual factors can impair system 2's ability to correct system 1's suggestions, increasing the likelihood of cognitive errors. This is particularly evident in high-stress environments like emergency departments.

4.3.3 Failure of system 2

Finally, errors can occur when system 2 cannot find the right diagnosis due to a knowledge gap (Raharjanti et al., 2021, p. 6). Without sufficient knowledge, system 2 will not be able to come to the right conclusion (Norman et al., 2017, p. 25).

The relative importance of the three discussed processes leading to diagnostic errors is strongly debated. While Croskerry argues that most errors occur within system 1 (Croskerry, 2009b, p. 32), Pelaccia et al. found inconsistent results in terms of the role of intuitive processes on diagnostic errors (Pelaccia et al., 2020, p. 210). Normal et al. underline that both, system 1 and system 2, can contribute to errors (Norman et al., 2017, p. 23). Raharjanti et al. argue, that although there are various reasons for errors in clinical reasoning, diagnostic errors are more likely due to errors in cognitive processes compared to knowledge gaps (Raharjanti et al., 2021, pp. 6–8). Acknowledging the possibility of multiple processes contributing to diagnostic errors, the specifics of junior doctors working in emergency departments regarding errors in clinical reasoning will be elaborated.

4.3.4 Impact on junior doctors in emergency departments

Junior doctors working in emergency departments are particularly susceptible to errors in clinical decision-making. This can be attributed to the challenges posed by the high-stress environment, as well as the constraints associated with their level of experience.

System 1 thinking, which relies on intuitive pattern recognition, can fail when there is a misinterpretation of a given clinical situation due to a lack of representative illness scripts stored in long-term memory. This is especially problematic for junior doctors who have limited experience and clinical knowledge (Croskerry, 2009b, p. 31; L. N. Medford-Davis et al., 2018, p. 1099). Consequently, junior doctors are more reliant on system 2 thinking.

The high-stress environment of emergency departments, characterized by time constraints and frequent interruptions, can lead to a high cognitive load for all clinicians (Croskerry, 2009a, p. 1025; L. N. Medford-Davis et al., 2018, p. 1098). For junior doctors, who rely heavily on system 2 thinking, this high cognitive load can be especially problematic. System 2 thinking demands a significant amount of mental resources, making junior doctors more susceptible to cognitive overload. Factors such as sleep deprivation due to night shifts can further negatively impact their cognitive performance, exacerbating the challenges they face in this demanding setting (Cleland et al., 2021, pp. 6–7). When junior doctors' system 2 thinking is overloaded, they may be forced to fall back on the default system 1 thinking (Pelaccia et al., 2020, p. 210), which is less reliable for them due to their limited experience and clinical knowledge. This situation increases the likelihood of errors in their decision-making, particularly when they have little time for diagnosis (Norman et al., 2017, p. 25).

In summary, junior doctors in emergency departments are especially vulnerable to errors due to the unique challenges posed by their work environment and their reliance on system 2 thinking. Personal and contextual factors, such as time constraints, sleep deprivation, and cognitive overload, can impair their ability to monitor and correct system 1's suggestions, increasing the likelihood of cognitive errors in clinical decision-making.

4.4 Summary of clinical reasoning

Clinical reasoning encompasses the decision-making process in a clinical setting, with this thesis specifically focusing on the diagnostic process through the lens of dual-process theory. In this context, pattern recognition and illness scripts are vital for generating an initial diagnosis, which falls under the domain of system 1 thinking. System 2 intervenes only when the initial process is inconclusive or evidently flawed, as it is tasked with monitoring and correcting system 1's suggestions. Clinical errors may arise if system 1’s suggestions are erroneous and system 2 fails to identify and rectify these inaccuracies. Junior doctors in emergency departments are particularly susceptible to errors due to their still-developing pattern recognition skills and the high-stress environment of emergency departments, which can result in cognitive overload and subsequent failure of system 2. Given the profound impact of diagnostic errors on individuals' lives (Committee on Diagnostic Error in Health Care et al., 2015, p. 1), it is crucial to identify and implement solutions to improve diagnostic accuracy. One such possible solution, the implementation of computerised clinical decision support systems (CDSS), will be explored in the next chapter.

5 Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) are vital tools used to assist and therefore enhance the decision-making process of physicians. CDSS aim to ultimately improve patient care and clinical performance (Muhiyaddin et al., 2020, p. 470; Souza-Pereira et al., 2021, p. 1). There has been a gradual rise in the adoption of health information technology as electronic health records (EHRs) continue to be implemented globally (Fernandes et al., 2020, p. 2). CDSS are aimed to improve healthcare delivery by helping physicians to make better decisions via incorporating targeted clinical knowledge, patient information, and other health information. They can be seen as software that uses information about the patient to present specific recommendations that help physicians in their decision-making while following the physicians workflow (Mills, 2019, p. 1; Peiffer-Smadja et al., 2020, p. 585; Sutton et al., 2020, p. 1). The objective of these systems is not to substitute physicians as decision-makers, but rather to offer relevant knowledge and assistance for their decision-making process (Fernandes et al., 2020, p. 2). The implementation of CDSS provides a range of advantages, including a decrease in misdiagnosis rates, enhanced efficiency, a reduction in medication errors, the facilitation of informed decision-making and higher confidence in the decision. Despite these benefits, there are also challenges, such as potential risks to clinical autonomy, significant expenses related to adoption and upkeep, challenges in aligning with intricate healthcare workflows, and limited compatibility with EHRs in certain standalone systems (Muhiyaddin et al., 2020, pp. 470, 471).

CDSS can be divided into knowledge-based systems and non-knowledge-based systems. (Araujo et al., 2020, p. 2; Légat et al., 2018, p. 6; Sutton et al., 2020, p. 1).

Knowledge-based CDSS are expert systems that rely on evidence-based rule databases, consisting of IF-THEN statements, to generate patient-specific assessments or recommendations. These rules can be set using literature-based, practice-based, or patient-directed evidence. The rule bases can be internally developed by organizations, or vendor supplied. In these systems, data is retrieved to evaluate rules, ultimately producing an action or output. Basic knowledge-based CDSS can provide alerts for potential drug allergies, while more complex systems integrate contextual information from the patient's electronic health record to generate tailored recommendations. Healthcare organizations ideally combine vendor-supplied rule sets with internally developed rules to maintain an up-to-date knowledge base that reflects the evolving clinical landscape. Regular review of the rule bases is recommended to ensure their usefulness and relevance (Légat et al., 2018, p. 6; Sutton et al., 2020, p. 1).

Non-knowledge-based CDSS, on the other hand, apply artificial intelligence (AI) techniques, such as machine learning (ML) and artificial neural networks, to generate recommendations. These systems were developed to overcome the limitations of rule-based systems, as they can define their own rules. Non-knowledge-based CDSS still require a data source but use AI algorithms to recognize patterns in the data rather than following predefined expert medical knowledge (Peiffer-Smadja et al., 2020, p. 585). With the progress of AI in the 1980s, AI tools were incorporated into decision support systems to increase their impact, leading to the emergence of intelligent decision support systems (i-DSS) as a sub-discipline of clinical support system research. Machine learning is a key technology within i-DSS research, enabling the systems to obtain new knowledge and adapt to the user or changing environment (Fernandes et al., 2020, p. 2). However, non-knowledge-based CDSS face challenges such as the "black box" issue, where understanding the logic behind AI-generated recommendations is difficult to impossible, and problems with data availability (Araujo et al., 2020, p. 2; Sutton et al., 2020, p. 1). One of the most critical issues when developing machine learning in a clinical setting is trust, where both clinicians and patients need to accept the recommendations provided by the system (Noorbakhsh-Sabet et al., 2019, p. 7). Widespread implementation of these systems has not yet been achieved, but continued advancements in AI and machine learning may help address these challenges in the future.

In summary, knowledge-based CDSS and non-knowledge-based systems differ in their approach to generating recommendations for healthcare professionals. Knowledge-based systems use evidence-based rules derived from clinical research and best practices, while non-knowledge-based systems rely on AI and machine learning techniques to analyse data and identify patterns. Both types of systems aim to improve the quality of care provided and reduce errors, but their effectiveness depends on the quality and relevance of the data and knowledge bases they utilize.

Although there is a wide range of literature on CDSS, many projects lacked the implementation phase (Fernandes et al., 2020, p. 1). Reliable data on the advantages of CDSS is therefore rare. In the following chapter, a short overview on current applications of CDSS will be given. Then, a theoretical framework of a specific use case for junior doctors in emergency departments will be elaborated.

5.1 Applications of CDSS – Overview

One application of clinical decision support systems is the enhancement of patient safety by reducing incidents of prescriptions and medication errors. Drug-Drug Interaction (DDI) errors, for example, are a common and preventable error. Computerized Physician Order Entry (CPOE) systems incorporate drug safety software to address dosing, therapy duplication, and DDI checking. Electronic drug dispensing systems (EDDS) and bar-code point-of-care medication administration systems further enhance patient safety by creating a closed loop, where each step in the medication process is computerized and connected. These systems can be combined with CPOE and CDSS, leading to reduced prescribing error rates in drug allergy detection, excessive dosing, and unclear ordering. One key issue with drug allergy alerts is, however, their low specificity, leading to high override rates of up to 90% and causing alert fatigue. Overall, CDSS targeting patient safety are one of the best tested applications and have been generally successful in reducing errors and contraindications, with patient safety being a secondary objective for most CDSS implementations (Légat et al., 2018, p. 2; Sutton et al., 2020, p. 2).

In clinical management, CDSS can increase adherence to guidelines by encoding rules into the system, assisting with research or treatment protocols, tracking orders, and identifying eligible patients for research. For cost containment, CDSS can improve cost-effectiveness by suggesting cheaper medication alternatives, reducing test duplication, and decreasing inpatient length-of-stay. Further, in administrative functions, CDSS support clinical and diagnostic coding, ordering procedures and tests, and improving patient triage and documentation accuracy, which aids clinical protocols and ensures proper patient care (Sutton et al., 2020, p. 5).

Clinical decision support systems for clinical diagnosis, also known as diagnostic decision support systems (DDSS), decision-making support systems (DMSS) or simply decision support system (DSS), are designed to aid decision-makers by providing interactive support throughout every stage of a physician's decision-making process. Applications in this area traditionally provide a computerized consultation step to generate a list of possible or probable diagnoses. However, their impact has been limited compared to other types of CDSS due to factors such as negative physician perceptions, biases, poor accuracy, and poor system integration requiring manual data entry. Improvements in EHR-integration and standardized vocabulary like SNOMED Clinical Terms are gradually addressing these issues. Considering the known incidence of diagnostic errors, there is a lot of hope for CDSS to enhance diagnostic accuracy. Currently, an increase in the development of diagnostic systems that utilize non-knowledge-based techniques, such as machine learning, can be seen. These systems could potentially lead to more precise diagnoses and therefore with the reduction of diagnostic errors to a better patient outcome (Fernandes et al., 2020, p. 2; Sutton et al., 2020, pp. 5, 6).

In addition to general assistance in the decision-making process, two subdomains where CDSS are used have emerged: diagnostic support for imaging and diagnostic support for laboratory tests and pathology (Sutton et al., 2020, p. 6).

Firstly, diagnostic support for imaging involves the use of knowledge-based CDSS for tasks such as image ordering. These systems aid radiologists in selecting the most appropriate tests, providing reminders of best practice guidelines, and alerting them to potential contraindications. Additionally, there is an increasing interest in non-knowledge-based CDSS for advanced imaging and precision radiology, or radiomics, which utilize AI technologies like deep learning to assist in data extraction, visualization, and interpretation. Leading companies in this domain include IBM Watson Health, DeepMind, and Google.

The second subdomain, diagnostic support in laboratory testing and pathology interpretation, highlights the versatility of CDSS. These systems can provide simple alerts and reminders for abnormal lab results and even enhance the accuracy of non-invasive diagnostic tests using AI models. Furthermore, CDSS can serve as interpretation tools when a test's reference ranges depend on personalized factors such as age, sex, or disease subtypes. In pathology, applications of CDSS include automated tumour grading, computerized ECG analysis, automated arterial blood gas interpretation, protein electrophoresis reports, and blood cell counting support.

Lastly, patient-facing decision support systems, integrated with Personal Health Records (PHRs), are increasingly becoming popular tools to facilitate shared decision-making between patients and healthcare providers. These systems enable patients to access and manage their health data, allowing for better engagement in their care. PHRs can be extensions of EHR software or standalone web-based or mobile applications. The range of data collected in PHRs is vast, including symptom tracking, allergies, insurance coverage, and medication information. Wearable health devices can also be integrated, offering providers actionable insights for patient care. As PHRs develop advanced CDSS capabilities, there is a growing emphasis on designing these systems to promote shared decision-making and empower patients to be more knowledgeable and involved in their care (Sutton et al., 2020, p. 6).

In conclusion, a wide array of CDSS is already being used and tested in various domains, such as patient safety, clinical management, clinical diagnosis, and patient-facing decision support systems. However, there are still problems that hinder their broad adoption. Despite the success of CDSS in improving patient safety, issues like low specificity in drug allergy alerts and alert fatigue need to be addressed. In clinical diagnosis, negative physician perceptions, especially among the more experienced physicians, biases, poor accuracy, and poor system integration limit the impact of these systems, although advancements in EHR-integration and standardized vocabulary are gradually resolving these issues. The subdomains of diagnostic support for imaging and laboratory tests and pathology are experiencing rapid growth, with AI technologies like deep learning playing a crucial role. Patient-facing decision support systems integrated with Personal Health

Records (PHRs) aim to facilitate shared decision-making between patients and healthcare providers, but further development of CDSS capabilities within these systems is needed to better engage patients. Nevertheless, there is hope that continuous advancements in CDSS technology will overcome current and future challenges. Baartmans et al. emphasized the potential benefits of implementing CDSS to aid in the diagnostic process, suggesting that it could lead to a reduction in mistakes (Baartmans et al., 2022, p. 1140). Building on this notion, the following chapter will delve into a theoretical framework for a CDSS providing probable differential diagnoses, which has the potential to significantly enhance the decision-making process of junior doctors in emergency departments, ultimately leading to improved patient outcomes.

5.2 CDSS for junior doctors in emergency departments – a framework

In this final section, a theoretical framework will be developed to elucidate how a specially designed or trained model could assist junior physicians in emergency departments with their decision-making process. Identifying the correct diagnosis is crucial, not only for older patients, where discrepancies between admission and discharge diagnoses are associated with longer hospital stays, but for all patients (Avelino-Silva & Steinman, 2020, p. 1). As Baartmans et al. stated, the majority of human errors are categorized as mistakes, primarily taking place in the assessment phase and throughout the interpretation of test results. Enhancing the diagnosing process may yield substantial benefits in terms of reducing errors and therefore improving patient outcomes. The following framework will discuss a CDSS that might help young physicians in the process of coming to the right diagnosis by providing a list of probable differential diagnoses.

One of the differences in decision-making between junior doctors and their experienced colleges is that junior doctors must rely on system 2 thinking. This is because they did not have the time to build a vast database of illness scripts, mental representations of diseases, which are required for system 1 to match a case at hand with one of the memorised diseases. However, system 2 has only a limited amount of mental resources available in its working memory. If the current task or situation leads to cognitive overload, which occurs when the working memory is depleted, system 2 fails, and the decision-making process defaults back to system 1 thinking. A failure of system 2 and subsequent reliance on system 1 is especially detrimental in junior doctors due to their limited training.

In emergency departments, there are many external factors that may lead junior doctors system 2's to overload. First, constant interruptions, which are common in EDs, have been shown to increase the cognitive load of physicians. Secondly, sleep deprivation is a major contributor to system 2 failure. This can be especially detrimental since in many emergency departments it is the junior doctors that are mainly responsible for the night shifts. Thirdly, physicians in emergency departments frequently need to manage multiple patients simultaneously, which can strain their working memory. Moreover, maintaining numerous differential diagnoses for each patient further taxes system 2 and may lead to cognitive dissonance, the psychological discomfort experienced when holding conflicting thoughts concurrently. Because of this psychological discomfort, the physicians holding the concurring thoughts might be tempted to reject most of the differential diagnoses as soon as possible. Considering a broad spectrum of relevant differential diagnoses is, however, important, as Medford-Davis et al. found that errors in emergency departments were more likely to occur when the true diagnosis was not part of the considered differential diagnoses (L. Medford-Davis et al., 2016, p. 4). Lastly, time pressure in the emergency department represents a significant constraint, often causing junior doctors to cut corners in the assessment process in order to avoid delays. Time pressure discourages the use of checkpoint strategies and reflective diagnostic time-outs. These constraints all can contribute to potential errors in diagnosis.

In summary, the diagnostic process is vital for preventing errors and, consequently, improving patient outcomes. Junior doctors rely on system 2 thinking, which can easily fail due to cognitive overload, especially in the specific setting of emergency departments. As such, a clinical decision support system is needed to address this issue.

The author proposes developing a CDSS that focuses on providing a list of the most probable differential diagnoses based on the patient's presentation.

The CDSS should be integrated with the electronic health record, so general information about the patient, including age, weight, medical history, allergies and current medication, can be used in the algorithm. Additionally, the physician should be able to input current symptoms.

The method of processing the physician's inputs can be influenced in the development of the system by local preferences. On the one hand, a knowledge-based system may be chosen; however, generating rules for this approach could be laborious due to the vast array of symptoms and patient profiles. It may not be feasible to cover every possible outcome with a knowledge-based system. If this approach is preferred, developers might opt to focus on symptom-centred programming, excluding general patient information. Consequently, the generated list would be based solely on current symptoms, simplifying the programming but potentially lacking specificity. For instance, if a young patient presents to the ED with blood in their stool, the tool might suggest colorectal cancer, which is improbable in younger patients. However, this approach offers the advantage of trust, as the rule-based system is developed by experts. Additionally, the absence of a "black box" means that the provided lists are traceable and adjustable if necessary.

On the other hand, if physicians prefer a system that can learn and adapt to diverse patient presentations, the CDSS could be designed using artificial intelligence and machine learning techniques. These approaches can learn from vast amounts of data, allowing the CDSS to consider both general patient information and specific symptoms when generating a list of potential diagnoses. This integration of patient-specific information makes the system more tailored to individuals, resulting in more accurate diagnostic suggestions. For example, in the case of a young patient presenting to the ED with blood in their stool, an AI/ML-based CDSS would consider the patient's age and other relevant factors, making it less likely to suggest colorectal cancer as a probable diagnosis. This approach allows the CDSS to continuously learn and improve its diagnostic suggestions based on real-world data and outcomes. However, there are some challenges associated with AI/ML-based systems. The "black box" nature of these algorithms can make it difficult, if not impossible, to understand the reasoning behind the generated lists, potentially reducing trust in the system. Additionally, as with all systems that require training, the quality of the CDSS's performance is highly dependent on the quality and representativeness of the data used for training the model. To address these concerns, developers should train such models on diverse and high-quality datasets to maximize their effectiveness and reliability.

The decision, whether an expert-centric rule-based approach or a data-centric approach using AI should be implemented, should be made individually. Additionally, regional specifies, like regulations, must be considered.

Once the preferred approach has been established, the CDSS can be designed to provide a list displaying inclusion and exclusion criteria for each differential diagnosis, along with suggested testing methods. For example, if the list included myocardial infarction, the CDSS would advise the junior doctor to perform blood work to check troponin T levels and conduct an ECG to look for changes in repolarisation. The results of these tests will then help to confirm or rule out myocardial infarction as a possible diagnosis. This two-step process of providing a list of probable differential diagnoses first and the suggesting methods to confirm or rule out each diagnosis, could also be implemented using a hybrid system design. For instance, determining the appropriate differential diagnoses could be achieved through a machine learning model, while providing tailored testing recommendations could be based on rule-driven algorithms. Such a design offers the advantage of a universal ML model capable of evaluating the relevant differentials, which can be employed across various hospitals. Meanwhile, the rule-based suggestions for testing these differentials can be specifically adapted to each hospital's unique circumstances, such as the availability of particular testing facilities or resources. This hybrid approach combines the strengths of both ML and rule-based systems, resulting in a more effective and customizable CDSS.

There are several advantages to implementing a CDSS that helps junior doctors by providing probable differential diagnoses. First, CDSS can improve the confidence in a decision (Muhiyaddin et al., 2020, p. 471). This would be especially advantageous for junior doctors, since low confidence has been shown to negatively impact preparedness in medical graduates (Monrouxe et al., 2017, p. 2).

Second, it may relieve their burden of having to think about all the differential diagnoses, thereby reducing cognitive load. With this freed up cognitive capacity, junior doctors can concentrate on evaluating the provided list to determine the most accurate diagnosis, ultimately leading to the most effective treatment for the patient.

Further, due to the reduced cognitive load, system 2 is less likely to be overloaded. As a result, there is a decreased need to fall back on the default system 1 thinking. This reduction in reliance on system 1 thinking leaves junior doctors less susceptible to cognitive biases, further enhancing decision quality.

Finally, a well-designed CDSS can compensate for knowledge gaps that junior doctors may encounter due to their limited experience or unfamiliarity with certain conditions. By supplying a list of probable differential diagnoses and outlining the appropriate methods for confirming or ruling out each diagnosis, the CDSS serves as a valuable resource for enhancing clinical decision-making. This support allows junior doctors to make more informed decisions, even in cases where their own knowledge might be insufficient.

A clinical decision support system that helps junior doctors in emergency departments by providing a list of probable differential diagnoses might not only reduce errors and therefore improve patient outcomes but could also serve as a valuable educational tool. As junior doctors gain experience over time, they may eventually no longer require the assistance of the CDSS. This phenomenon, known as the carry-over effect, suggests that CDSSs have an inherently educational aspect. However, the literature on the impact of such learning mechanisms is divided. A counterargument posits that junior doctors might develop an excessive reliance or trust in the CDSS, potentially hindering their professional growth (Sutton et al., 2020, p. 7).

The proposed framework, while grounded in the literature reviewed for this thesis, remains theoretical in nature. To determine whether its promising outlook can be substantiated, it is essential to develop such a model and test it in a practical setting in order to evaluate its real-world performance and impact.

6 Conclusion

Dual-process theory states that human’s decision-making process is governed by two distinctive systems. System 1 is the fast, intuitive and energy-efficient system that mostly works beneath our conscious threshold. It is responsible for monitoring internal and external stimuli and making fast, intuitive decisions. These suggestions are controlled and corrected, if necessary, by system 2. System 2 is slow, analytical and deliberate. It is active when individuals engage in highly complex cognitive work and for doing so, requires significant amounts of energy. Therefore, our brain works most of the time with the default system 1 and system 2 is only engaged when necessary. This process generally works fine. It can, however, be prone to errors when system 1 makes the wrong suggestions and system 2 fails to detect and or correct it. Various systematic failures of this process have been described, including availability bias, confirmation bias and anchoring bias.

Clinical reasoning can be described using dual-process theory. When encountering a patient, system 1 makes an initial diagnosis by comparing the available information about the patient, like symptoms, past medical history and blood work, with stored illness scripts of representative cases in long-term memory. If a fitting match can be found, it is likely that the physician’s system 2 accepts it. If the initial evaluation turns out to be inconclusive, system 2 is engaged to come up with multiple hypotheses which are deductively being confirmed or ruled out by gathering additional data.

The clinical reasoning process of junior doctors in emergency departments is specific. On the one hand, since junior doctors lack experience and have therefore only a limited amount of representative illness scripts stored in long-term memory, they must rely on system 2 thinking. As working memory is limited in capacity, increased usage of system 2 thinking can lead to increased cognitive strain. This problem is amplified by the high-stress environment, with factors like constant interruptions, sleep deprivation and high time pressure all further increasing cognitive load. These factors can lead to cognitive overload with subsequent failure of system 2, leaving junior doctors with default mode system 1 thinking. As system 1 uses mental shortcuts, clinical errors can occur. Errors in the diagnostic process have been shown to potentially lead to devastating patient outcomes, with an estimation of most people experiencing at least one diagnostic error in their lifetime.

Clinical decision support systems might provide a solution to this urgent problem. They are already tested in various fields, ranging from increasing patient safety by reducing medication errors to image recognition based on artificial intelligence. One application is the assistance in the diagnostic process. Although the framework proposed in Chapter 5.2 is theoretical, it can be assumed that a specifically designed clinical decision support system that provides a list of probable differential diagnoses along with suggested testing methods to confirm or rule out a diagnosis has several advantages for junior doctors in emergency departments. Firstly, CDSS can boost decision-making confidence, which is particularly beneficial for junior doctors. Secondly, it can relieve the burden of considering all differential diagnoses, reducing cognitive load and allowing junior doctors to focus on evaluating the provided list for the most accurate diagnosis and effective treatment. Additionally, the reduced cognitive load can decrease the likelihood of system 2 overload, minimizing reliance on error-prone system 1 thinking and therefore reducing cognitive biases to enhance decision quality. Lastly, such a CDSS can even compensate for junior doctors' knowledge gaps by providing a list of probable differential diagnoses and relevant testing methods, enabling more informed decisions even when their own knowledge might be lacking. A well-designed CDSS holds the potential to revolutionize the diagnostic process by increasing diagnostic accuracy and reducing error rates, ultimately improving patient outcomes in emergency departments. To fully realize and evaluate this promising outlook, it is crucial to develop such a model and test it within a clinical setting.

7 References

Adams, E., Goyder, C., Heneghan, C., Brand, L., & Ajjawi, R. (2017). Clinical reasoning of junior doctors in emergency medicine: A grounded theory study. *Emergency Medicine Journal*, *34*(2), 70–75. https://doi.org/10.1136/emermed-2015-205650

Araujo, S. M., Sousa, P., & Dutra, I. (2020). Clinical Decision Support Systems for Pressure Ulcer Management: Systematic Review. *JMIR Medical Informatics*, *8*(10), e21621. https://doi.org/10.2196/21621

Audétat, M.-C., Laurin, S., Dory, V., Charlin, B., & Nendaz, M. R. (2017). Diagnosis and management of clinical reasoning difficulties: Part I. Clinical reasoning supervision and educational diagnosis. *Medical Teacher*, *39*(8), 792–796. https://doi.org/10.1080/0142159X.2017.1331033

Avelino-Silva, T. J., & Steinman, M. A. (2020). Diagnostic discrepancies between emergency department admissions and hospital discharges among older adults: Secondary analysis on a population-based survey. *Sao Paulo Medical Journal*, *138*(5), 359–367. https://doi.org/10.1590/1516-3180.0471.r1.05032020

Baartmans, M. C., Hooftman, J., Zwaan, L., van Schoten, S. M., Erwich, J. J. H. M., & Wagner, C. (2022). What Can We Learn From In-Depth Analysis of Human Errors Resulting in Diagnostic Errors in the Emergency Department: An Analysis of Serious Adverse Event Reports. *Journal of Patient Safety*, *18*(8), e1135–e1141. https://doi.org/10.1097/PTS.0000000000001007

Barrouillet, P. (2011). Dual-process theories and cognitive development: Advances and challenges. *Developmental Review*, *31*(2–3), 79–85. https://doi.org/10.1016/j.dr.2011.07.002

Brosnan, M., Lewton, M., & Ashwin, C. (2016). Reasoning on the Autism Spectrum: A Dual Process Theory Account. *Journal of Autism and Developmental Disorders*, *46*(6), 2115–2125. https://doi.org/10.1007/s10803-016-2742-4

Cleland, J., Gates, L. J., Waiter, G. D., Ho, V. B., Schuwirth, L., & Durning, S. (2021). Even a little sleepiness influences neural activation and clinical reasoning in novices. *Health Science Reports*, *4*(4). https://doi.org/10.1002/hsr2.406

Coen, M., Sader, J., Junod-Perron, N., Audétat, M.-C., & Nendaz, M. (2022). Clinical reasoning in dire times. Analysis of cognitive biases in clinical cases during the COVID-19 pandemic. *Internal and Emergency Medicine*, *17*(4), 979–988. https://doi.org/10.1007/s11739-021-02884-9

Committee on Diagnostic Error in Health Care, Board on Health Care Services, Institute of Medicine, & The National Academies of Sciences, Engineering, and Medicine. (2015). *Improving Diagnosis in Health Care* (E. P. Balogh, B. T. Miller, & J. R. Ball, Eds.; p. 21794). National Academies Press. https://doi.org/10.17226/21794

Croskerry, P. (2009a). A Universal Model of Diagnostic Reasoning: *Academic Medicine*, *84*(8), 1022–1028. https://doi.org/10.1097/ACM.0b013e3181ace703

Croskerry, P. (2009b). Clinical cognition and diagnostic error: Applications of a dual process model of reasoning. *Advances in Health Sciences Education*, *14*(S1), 27–35. https://doi.org/10.1007/s10459-009-9182-2

Croskerry, P. (2017). A Model for Clinical Decision-Making in Medicine. *Medical Science Educator*, *27*(S1), 9–13. https://doi.org/10.1007/s40670-017-0499-9

Durning, S. J., Dong, T., Artino, A. R., Van der Vleuten, C., Holmboe, E., & Schuwirth, L. (2015). Dual processing theory and experts' reasoning:

Exploring thinking on national multiple-choice questions. *Perspectives on Medical Education*, *4*(4), 168–175. https://doi.org/10.1007/S40037-015-0196-6

Evans, J., & Frankish, K. (Eds.). (2009). *In two minds: Dual processes and beyond* (1st ed.). Oxford University PressOxford. https://doi.org/10.1093/acprof:oso/9780199230167.001.0001

Evans, J. St. B. T. (2019). Reflections on reflection: The nature and function of type 2 processes in dual-process theories of reasoning. *Thinking & Reasoning*, *25*(4), 383–415. https://doi.org/10.1080/13546783.2019.1623071

Evans, J. St. B. T., & Stanovich, K. E. (2013). Dual-Process Theories of Higher Cognition: Advancing the Debate. *Perspectives on Psychological Science*, *8*(3), 223–241. https://doi.org/10.1177/1745691612460685

Fernandes, M., Vieira, S. M., Leite, F., Palos, C., Finkelstein, S., & Sousa, J. M. C. (2020). Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: A Review. *Artificial Intelligence in Medicine*, *102*, 101762. https://doi.org/10.1016/j.artmed.2019.101762

Grayot, J. D. (2020). Dual Process Theories in Behavioral Economics and Neuroeconomics: A Critical Review. *Review of Philosophy and Psychology*, *11*(1), 105–136. https://doi.org/10.1007/s13164-019-00446-9

Harris, E., & Santhosh, L. (2022). Dual Process Theory and Cognitive Load. *Critical Care Clinics*, *38*(1), 27–36. https://doi.org/10.1016/j.ccc.2021.07.001

Kahneman, D. (2011). *Thinking, fast and slow* (1st ed). Farrar, Straus and Giroux.

Légat, L., Van Laere, S., Nyssen, M., Steurbaut, S., Dupont, A. G., & Cornu, P. (2018). Clinical Decision Support Systems for Drug Allergy Checking:

Systematic Review. *Journal of Medical Internet Research*, *20*(9), e258. https://doi.org/10.2196/jmir.8206

Linn, A., Khaw, C., Kildea, H., & Tonkin, A. (2012). *Clinical reasoning: A guide to improving teaching and practice*.

Marcum, J. A. (2012). An integrated model of clinical reasoning: Dual-process theory of cognition and metacognition: Integrated model of clinical reasoning. *Journal of Evaluation in Clinical Practice*, *18*(5), 954–961. https://doi.org/10.1111/j.1365-2753.2012.01900.x

Medford-Davis, L. N., Singh, H., & Mahajan, P. (2018). Diagnostic Decision-Making in the Emergency Department. *Pediatric Clinics of North America*, *65*(6), 1097–1105. https://doi.org/10.1016/j.pcl.2018.07.003

Medford-Davis, L., Park, E., Shlamovitz, G., Suliburk, J., Meyer, A. N., & Singh, H. (2016). Diagnostic errors related to acute abdominal pain in the emergency department. *Emergency Medicine Journal*, *33*(4), 253–259. https://doi.org/10.1136/emermed-2015-204754

Mills, S. (2019). Electronic Health Records and Use of Clinical Decision Support. *Critical Care Nursing Clinics of North America*, *31*(2), 125–131. https://doi.org/10.1016/j.cnc.2019.02.006

Miyagami, T., Watari, T., Harada, T., & Naito, T. (2023). Medical Malpractice and Diagnostic Errors in Japanese Emergency Departments. *Western Journal of Emergency Medicine*, *24*(2), 340–347. https://doi.org/10.5811/westjem.2022.11.55738

Monrouxe, L. V., Grundy, L., Mann, M., John, Z., Panagoulas, E., Bullock, A., & Mattick, K. (2017). How prepared are UK medical graduates for practice? A rapid review of the literature 2009–2014. *BMJ Open*, *7*(1), e013656. https://doi.org/10.1136/bmjopen-2016-013656

Muhiyaddin, R., Abd-Alrazaq, A. A., Househ, M., & Shah, Z. (2020). *The Impact of Clinical Decision Support Systems (CDSS) on Physicians: A Scoping Review*.

Noorbakhsh-Sabet, N., Zand, R., Zhang, Y., & Abedi, V. (2019). Artificial Intelligence Transforms the Future of Health Care. *The American Journal of Medicine*, *132*(7), 795–801. https://doi.org/10.1016/j.amjmed.2019.01.017

Norman, G. R., Monteiro, S. D., Sherbino, J., Ilgen, J. S., Schmidt, H. G., & Mamede, S. (2017). The Causes of Errors in Clinical Reasoning: Cognitive Biases, Knowledge Deficits, and Dual Process Thinking. *Academic Medicine*, *92*(1), 23–30. https://doi.org/10.1097/ACM.0000000000001421

Peiffer-Smadja, N., Rawson, T. M., Ahmad, R., Buchard, A., Georgiou, P., Lescure, F.-X., Birgand, G., & Holmes, A. H. (2020). Machine learning for clinical decision support in infectious diseases: A narrative review of current applications. *Clinical Microbiology and Infection*, *26*(5), 584–595. https://doi.org/10.1016/j.cmi.2019.09.009

Pelaccia, T., Plotnick, L. H., Audétat, M.-C., Nendaz, M., Lubarsky, S., Torabi, N., Thomas, A., Young, M., & Dory, V. (2020). A Scoping Review of Physicians' Clinical Reasoning in Emergency Departments. *Annals of Emergency Medicine*, *75*(2), 206–217. https://doi.org/10.1016/j.annemergmed.2019.06.023

Pelaccia, T., Tardif, J., Triby, E., & Charlin, B. (2011). An analysis of clinical reasoning through a recent and comprehensive approach: The dual-process theory. *Medical Education Online*, *16*(1), 5890. https://doi.org/10.3402/meo.v16i0.5890

Preisz, A. (2019). Fast and slow thinking; and the problem of conflating clinical reasoning and ethical deliberation in acute decision-making. *Journal of Paediatrics and Child Health*, *55*(6), 621–624. https://doi.org/10.1111/jpc.14447

Raharjanti, N. W., Wiguna, T., Purwadianto, A., Soemantri, D., Bardosono, S., Poerwandari, E. K., Mahajudin, M. S., Ramadianto, A. S., Alfonso, C. A., Findyartini, A., Nugrahadi, N. R., Lazuardi, M. Q., Subroto, P. A. M., Saroso, O. J. D. A., & Levania, M. K. (2021). Clinical Reasoning in Forensic Psychiatry: Concepts, Processes, and Pitfalls. *Frontiers in Psychiatry*, *12*, 691377. https://doi.org/10.3389/fpsyt.2021.691377

Souza-Pereira, L., Ouhbi, S., & Pombo, N. (2021). Quality-in-use characteristics for clinical decision support system assessment. *Computer Methods and Programs in Biomedicine*, *207*, 106169. https://doi.org/10.1016/j.cmpb.2021.106169

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *Npj Digital Medicine*, *3*(1), 17. https://doi.org/10.1038/s41746-020-0221-y

Thampy, H., Willert, E., & Ramani, S. (2019). Assessing Clinical Reasoning: Targeting the Higher Levels of thePyramid. *Journal of General Internal Medicine*, *34*(8), 1631–1636. https://doi.org/10.1007/s11606-019-04953-4