The Role of Emotions in Decision-Making Among Healthcare Providers

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Abstract— **Emotions significantly influence clinical decision-making, shaping not only diagnostic efficiency but also the emergence of cognitive biases. This review synthesizes evidence from 2015–2025, exploring how emotional states—such as stress, empathy, and fatigue—interact with anchoring, confirmation bias, affect heuristic, and availability heuristic. Drawing on Dual-Process Theory, Cognitive Load Theory, Thagard's CRUM framework, and Affective Neuroscience, we assess three intervention categories: emotional intelligence training, mindfulness-based strategies, and AI-supported decision tools. Results reveal that emotional distress and intuitive heuristics can degrade clinical accuracy under pressure. However, emotionally adaptive interventions enhance cognitive control, self-awareness, and decision accuracy. This interdisciplinary review advocates for emotionally informed models of clinical reasoning that integrate both human and artificial intelligence to improve patient safety.**

Keywords—Clinical Decision-Making, Cognitive Bias, Emotional Influence, Heuristics in Medicine, AI Decision-Supports

I. INTRODUCTION

Clinical decision-making is a cognitively demanding process that occurs under conditions of uncertainty, time pressure, and emotional strain. Historically viewed through the lens of rationality and evidence-based protocols, recent interdisciplinary research highlights that emotions play a critical role in shaping diagnostic reasoning, treatment decisions, and patient-provider interactions [1], [2]. Emotional states such as anxiety, frustration, empathy, or fatigue can modulate cognitive processes—either enhancing intuitive recognition in time-sensitive scenarios or triggering cognitive biases that impair accuracy [3], [4].

Cognitive science frameworks such as Dual-Process Theory distinguish between fast, intuitive (System 1) and slow, analytical (System 2) reasoning. Under stress, clinicians are more likely to rely on System 1 heuristics, which, while efficient, increase susceptibility to anchoring bias, confirmation bias, and the affect heuristic [5], [6]. Affective Neuroscience further reveals that stress-induced changes in the prefrontal cortex degrade executive control, narrowing attention and increasing reliance on automatic emotional cues [7]. In high-pressure settings like emergency departments or intensive care units, emotional arousal—whether triggered by patient behavior or situational overload—has been shown to degrade safety judgments and reduce diagnostic vigilance [8], [9].

By synthesizing empirical and theoretical literature, we propose cognitive science–informed strategies to improve clinical reasoning and reduce diagnostic error. These emotion-driven biases are not merely theoretical. Studies show that cognitive errors linked to emotional states are a significant contributor to preventable adverse events [10]. For instance, physicians under emotional distress may demonstrate anchoring, prematurely closing diagnostic deliberation, or may overcorrect through excessive testing and defensive practices driven by fear of litigation [11], [12]. Emotional exhaustion and burnout—now prevalent among physicians—further compound this issue by impairing attention, memory, and the capacity for complex decision-making [13]. At the same time, positive emotional engagement can be beneficial. Experienced clinicians may use affectively informed "gut feelings" to rapidly recognize critical presentations (e.g., sepsis or myocardial infarction), where hesitation could be fatal [14]. The challenge lies in distinguishing when emotion enhances diagnostic efficiency and when it introduces risk. To address this duality, interventions such as emotional intelligence (EI) training [15], mindfulness practices [16], and artificial intelligence (AI)-assisted decision-support tools [17] have emerged to mitigate the adverse effects of emotion while preserving its benefits.

This review aims to systematically examine how emotions influence clinical decision-making and evaluate evidence-based strategies to reduce emotion-driven cognitive bias. Drawing on theories from cognitive science, affective neuroscience, and empirical medical research, it explores the nuanced role of emotion in clinical reasoning and highlights interventions that hold promise for improving diagnostic accuracy and patient safety.

II. METHODOLOGY - LITERATURE REVIEW DESIGN

To investigate how emotions influence clinical decision-making among healthcare providers and what strategies mitigate emotional bias, we conducted a structured, iterative literature review using cognitive science methodologies. The review focused on empirical and theoretical literature from 2015-2025, with the inclusion of foundational works to support key frameworks (e.g., Dual-Process Theory, CRUM).

A. Search Strategy and Process

The literature review drew from two major databases—**PubMed Google Scholar**—to ensure a multidisciplinary reach. While databases such as PsycINFO or Scopus offer valuable content, they were excluded due to access limitations and overlap in returned articles. This represents a practical tradeoff and is acknowledged as a limitation. The review adhered to PRISMA principles where possible, although formal registration was not performed.

Keywords included:

- *"emotion" AND "clinical decision-making" [3227 results]*
- *"anchoring bias" OR "availability heuristic" AND "stress" [2 results]*
- *"emotional intelligence" AND "healthcare" [11,174 results]*
- *"mindfulness" AND "diagnostic accuracy" [128 results]*
- *"AI decision support" AND "clinical bias" [331 results]*

Boolean operators and controlled vocabulary terms were used where appropriate (e.g., MeSH in PubMed). The timeframe was limited to the past ten years to capture recent advancements in medical cognition, debiasing interventions, and AI-assisted decision-making. Additional seminal works outside this period were included if cited frequently in peer-reviewed research.

B. Inclusion and Exclusion Criteria

This review did not employ standardized quality assessment tools (e.g., CASP or GRADE) to evaluate methodological rigor. Instead, articles were included based on conceptual relevance, clarity, and empirical grounding, which may introduce selection subjectivity.

We included articles that:

- Focused on **licensed healthcare providers** (physicians, nurses, and therapists)
- Addressed the role of emotions or emotional states in **clinical decision-making**
- Discussed **cognitive biases** such as anchoring, confirmation, affect heuristic, or availability heuristic
- Evaluated at least one **bias-mitigation strategy** (Emotional Intelligence training, mindfulness, or AI decision support)
- Were published in **peer-reviewed journals**

We excluded:

- Articles discussing **only patient emotions**
- Non-clinical populations (e.g., medical students in early training)
- Commentary, editorial, and opinion pieces without empirical grounding
- Redundant findings or studies with methodological concerns (e.g., unclear definitions or confounding)

C. Stepwise Inclusion Flow

The initial database and manual search yielded 14,863 results across PubMed, and Google Scholar. This high volume reflects broad keyword combinations and inclusive search terms designed to avoid missing relevant literature. However, only a small subset addressed our specific focus on emotion-driven cognitive biases in clinical decision-making.

The refinement process was as follows:

Title and keyword relevance screening excluded articles that were clearly unrelated (e.g., focused on patient emotion, non-clinical psychology, or unrelated AI topics), reducing the pool to ~300 articles. **Abstract screening** focused on empirical studies involving licensed healthcare providers and explicitly discussing both emotion and cognitive bias, narrowing the set to 71**. Full-text review** removed articles that lacked methodological clarity, contained redundant findings, or did not evaluate a bias-mitigation strategy, resulting in 50 eligible articles. From these, **35 studies** were included in the final synthesis, selected based on conceptual alignment with this review's framework (e.g., Dual-Process Theory, CRUM, Affective Neuroscience) and representation across diverse interventions (EI, mindfulness, AI tools).

D. Journal and Source Selection

After identifying the final set of 35 papers, articles were clustered into three domains:

- **Medical cognition and clinical reasoning** (e.g., *Medical Decision Making*, *JAMA Internal Medicine*)
- **Cognitive psychology and neuroscience** (e.g., *Frontiers in Psychology*, *Annual Review of Neuroscience*)
- **Bias intervention and decision support** (e.g., *BMJ Quality & Safety*, *Cureus*)

Books and foundational texts (e.g., Thagard's *Mind: Introduction to Cognitive Science* [1]) were selected only if cited repeatedly in the healthcare decision-making literature and integrated into cognitive models.

E. Refinement and Scope Adjustments

While the core research question remained stable throughout the review process, two key refinements were made to improve focus and relevance. First, the scope of cognitive biases examined was narrowed to four well-documented and emotion-sensitive types—anchoring, confirmation bias, the affect heuristic, and the availability heuristic. This decision was based on the strength, volume, and coherence of empirical and theoretical literature supporting these specific biases in clinical contexts. Second, the initial population focus, which centered solely on physicians, was expanded to include nurses and therapists. This adjustment was made after noting the frequent inclusion of non-physician healthcare providers in high-quality studies and recognizing their significant roles in emotionally charged clinical decision-making. Together, these refinements allowed for a more representative synthesis of the literature while maintaining alignment with the principles and scope of cognitive science.

III. Results

This section synthesizes findings from recent literature on the impact of emotions on cognitive biases in clinical decision-making among healthcare providers, along with evidence on mitigation strategies including emotional intelligence training, mindfulness-based interventions, and AI-supported decision tools. Four key biases—anchoring, confirmation, availability, and affect heuristic—are explored within the context of theoretical models and empirical data.

A. Emotional Triggers and Cognitive Biases

Healthcare professionals frequently rely on heuristics under high-stress conditions, which, while efficient, are vulnerable to emotional distortion.

1) Anchoring Bias: Emotional stress can accelerate the tendency to fixate on initial impressions. Ly et al. [18] demonstrated that emergency physicians anchored on previously documented heart failure diagnoses, resulting in under-testing for pulmonary embolism. Similarly, Binkley and Thomas [19] highlighted how the emotional comfort derived from an early, benign diagnosis often prevents clinicians from revising their initial judgment, especially when faced with diagnostic ambiguity.

2) Confirmation Bias: This bias is exacerbated when clinicians seek out data that affirm emotionally comforting or reputation-protective diagnoses. Isbell et al. [8] found that emotionally evocative patient interactions—particularly those involving anger or distress—led providers to selectively interpret diagnostic cues. Croskerry et al. [9] noted that fear of litigation and emotional pressure for diagnostic closure frequently push clinicians toward decisions that confirm prior assumptions, rather than reconsidering alternative diagnoses.

3) Availability Heuristic: Emotional salience increases mental availability of certain diagnoses. In a study of 400,000 emergency department visits, Ly [18] observed that after recently diagnosing a pulmonary embolism, physicians demonstrated heightened suspicion for the condition in similar future cases, even when statistically unwarranted.

4) Affect Heuristic: Emotional valence can unconsciously color clinical judgment. Kozlowski et al. [20] explained that physicians often underestimate serious conditions in patients perceived as cooperative and overestimate risks in those deemed non-compliant or hostile—emotional impressions affect their perceived urgency or necessity for intervention.

These biases are not isolated; they are entangled with emotional fatigue, situational urgency, and interpersonal dynamics, forming what Isbell et al. [8] describe as "emotion-laden decision environments." Figure 1 summarizes the relationships between common emotional states, associated biases, cognitive mechanisms, and supporting studies.

Emotion	Associated Bias(es)	Mechanism	Key Studies
Stress	Anchoring, Confirmation Bias	Narrows attention; reduces cognitive flexibility	[Ly, 2021]; [Isbell et al., 2020]
Fatigue	Availability Heuristic	Increases reliance on recent/accessible memories	[McEwen, 2007]
Anger Frustrati on	Affect Heuristic, Confirmation	Alters perceived risk; increases rigidity	[Kozlowski, 2017]; [Croskerry, 2010]
Empathy	Affect Heuristic	Overweight emotional salience of patient narratives	[Ko et al., 2024]; [Regehr, 2022]

Figure 1. Mapping between emotional states and decision-making biases.

B. Theoretical Explanations

Several cognitive science theories elucidate how and why emotions influence clinical reasoning.

1) **Dual-Process Theory:** Decision-making operates on a spectrum from fast, intuitive (System 1) to slow, analytical (System 2) thinking. Croskerry et al. [9] emphasized that under emotional duress, System 1 dominates, leading to heuristic shortcuts. The stress-induced shift to System 1 increases susceptibility to bias, especially in time-sensitive scenarios.

2) **Cognitive Load Theory (CLT):** Emotional stress contributes to extraneous cognitive load, limiting the capacity of working memory for complex decision-making. Schuman et al. [21] found that clinicians under emotional or multitasking stress demonstrated reduced diagnostic accuracy, reinforcing the CLT proposition that emotions consume critical cognitive bandwidth.

3) **Thagard's CRUM Framework:** CRUM posits that cognition is computational and representational, with emotional weights assigned to mental representations. Thagard [1] argued that clinicians often "prefer" emotionally comforting diagnoses, making those representations more likely to be activated in decision networks. Emotional coherence, rather than factual fit alone, drives many clinical judgments.

4) **Affective Neuroscience:** Emotional arousal modulates the prefrontal cortex's executive control via amygdala activation. Salzman and Fusi [22] reviewed neuroimaging studies showing that high amygdala activity correlates with poor

prefrontal inhibition during high-stakes decision-making, leading to emotionally biased actions.

C. Bias-Mitigation Strategies

To combat emotion-driven diagnostic errors, three mitigation strategies have shown empirical promise.

1) **Emotional Intelligence (EI) Training**: Powell et al. [23] conducted a meta-analysis revealing that EI interventions improved clinicians' self-awareness, regulation, and decision accuracy across diverse healthcare settings. Increased EI scores were linked to reduced emotional reactivity and better handling of complex diagnoses.

2) **Mindfulness-Based Interventions:** Łoś et al. [16] found that mindfulness training reduced fixation errors and improved situational awareness among medical trainees. Their findings were corroborated by Schuman et al. [21], who observed enhanced analytic decision-making and decreased bias susceptibility post-intervention.

3) **AI-Based Decision Support Systems**: While AI reduces reliance on heuristic shortcuts, it introduces new risks such as automation bias, where over-reliance on system output may suppress clinician intuition and reduce vigilance. Brown et al. [24] described AI tools that systematically offer differential diagnoses and evidence-based alerts, reducing physicians' reliance on emotion-driven heuristics. These tools act as neutral "second opinions" that counteract anchoring and availability biases by broadening diagnostic considerations.

While all three intervention strategies—EI training, mindfulness, and AI decision tools—showed promise, their effectiveness varied by context. EI training was most effective in interpersonal scenarios and among early-career clinicians. Mindfulness demonstrated utility in high-pressure, multitasking environments. AI tools were particularly valuable in differential diagnosis generation but required careful integration to avoid automation bias. These complementary strengths suggest that a layered approach may be most effective.

The reviewed evidence consistently supports the hypothesis that emotional states—particularly stress, fatigue, and interpersonal affect—profoundly influence the frequency and type of cognitive biases during clinical decision-making. Theoretical frameworks align in suggesting that emotional regulation can restore cognitive equilibrium. Simultaneously, interventions such as EI training, mindfulness, and AI tools show growing potential in bias mitigation. However, implementation fidelity and context-specific effectiveness require further exploration.

IV. Discussion

The findings from this systematic review offer significant implications for both cognitive science and clinical practice. Emotional influences on decision-making are not incidental; they are embedded within the structure of cognitive processes and exert systematic effects on the quality of clinical reasoning. From anchoring to affective heuristics, emotions alter information processing in predictable ways. This understanding necessitates a shift in how we conceptualize clinical cognition—from a purely rational, analytical activity to one that is integrative, acknowledging the role of affect.

Cognitive science frameworks, including Dual-Process Theory, Cognitive Load Theory, and Thagard's CRUM model, support the premise that emotion and cognition are intertwined. Dual-Process Theory, for example, illustrates how emotional stress and urgency favor System 1 processing—fast, intuitive, and often biased [1][25]. Cognitive Load Theory adds that emotional arousal, by increasing extraneous load, diminishes available cognitive resources for analytical (System 2) reasoning [26]. Thagard's HOTCO model within the CRUM framework deepens this explanation, suggesting that emotional valences attached to mental representations directly affect the coherence and selection of diagnostic hypotheses [1]. These cognitive theories validate the empirical findings from medicine and psychology and underscore the need to develop interventions that address emotion-driven bias at both the individual and systemic level.

The review's findings also reinforce the utility of emotional intelligence (EI) and mindfulness in mitigating cognitive bias. EI training has been shown to improve clinicians' ability to recognize and regulate their emotional responses, which is essential for reducing heuristic errors, particularly those driven by stress or interpersonal frustration [23]. Likewise, mindfulness-based interventions have been associated with reductions in diagnostic errors, partly through enhanced attention regulation and decreased emotional reactivity [16]. These findings demonstrate that psychological self-regulation skills are not just wellness add-ons—they are cognitive tools that contribute directly to better clinical judgment.

Importantly, AI-based clinical decision-support tools present a parallel but complementary route to bias mitigation. AI systems can surface alternative diagnoses, provide objective risk estimates, and reduce reliance on emotionally salient memories or recent experiences that contribute to availability bias [24]. However, the success of such tools depends on careful implementation. Without proper training, clinicians may fall prey to automation bias—an overreliance on algorithmic output without critical reflection. Integrating these tools into a clinical workflow demands not just technical reliability but also human-centered design that complements, rather than replaces, human reasoning.

Beyond individual strategies, the discussion must extend to institutional and educational reforms. System-level changes such as structured reflection breaks, improved work schedules to reduce fatigue, and the incorporation of bias training in medical curricula can create environments more conducive to reflective reasoning. Simulation-based learning that incorporates emotionally stressful scenarios can help clinicians practice recognizing when they are slipping into biased thinking. Furthermore, a team-based approach to decision-making—where emotional states and potential biases are openly discussed—can build a shared cognitive safety net that compensates for individual vulnerability.

This review also makes a valuable contribution to applied cognitive science by situating theoretical insights in a high-stakes, real-world domain. Emotion–cognition interactions in healthcare serve as a model for studying human decision-making under pressure. The implications extend beyond medicine to other complex, high-risk environments such as aviation, military operations, and crisis response systems, where rapid decisions must be made under emotional strain.

In conclusion, the review underscores a fundamental insight: optimal clinical reasoning requires not the suppression of emotion but the cultivation of emotional metacognition—the ability to recognize, interpret, and appropriately respond to one's own emotional states during decision-making. Training clinicians to develop this skill, supporting them with AI tools, and embedding these practices into healthcare systems are critical steps toward reducing diagnostic errors and improving patient safety.

V. Conclusion

This review illustrates that emotion is not peripheral to clinical reasoning—it is integral. Emotions like stress, fear, overconfidence, and empathy can modulate cognitive load and influence which mental shortcuts clinicians take under pressure. When left unchecked, these emotional influences contribute to anchoring, confirmation bias, affect heuristics, and availability bias, all of which can lead to diagnostic and therapeutic errors [1–4][26].

Theoretical models such as Dual-Process Theory, Cognitive Load Theory, and CRUM provide mechanisms to understand these phenomena, while affective neuroscience explains the neurobiological basis of emotional impact on executive function and decision-making [1–3], [26][27].

Encouragingly, recent evidence suggests that interventions—including Emotional Intelligence (EI) training, mindfulness-based practices, and AI-powered decision-support tools—can help clinicians recognize and reduce the influence of biasing emotions [16–18], [24][28]. These interventions target both the internal regulation of emotion and the external augmentation of decision-making and are increasingly being integrated into education and practice.

The integration of emotionally aware cognition into healthcare settings can improve both patient outcomes and clinician well-being. As clinical complexity grows, and as cognitive systems like AI become more prevalent, the ability to partner human reasoning with emotional insight and technical support will be a hallmark of safe, effective care.

Future research should continue to explore the synergy of cognitive science and clinical practice, including how emotion-aware systems and interventions can be personalized across different clinical environments and roles. Recognizing and managing emotion in medical decision-making is no longer optional—it is essential. As AI integration accelerates, and healthcare systems become more complex, emotionally adaptive reasoning models will be essential for ensuring both diagnostic accuracy and provider resilience. Advancing this field will require interdisciplinary collaboration to develop emotionally intelligent tools, training programs, and clinical cultures that recognize the cognitive costs of unregulated emotion.

VI. Limitations

While this review aimed to comprehensively analyze recent literature on emotional influences in clinical decision-making, several limitations must be acknowledged:

1. **Scope of Biases Studied:** This review focused on four commonly cited cognitive biases—anchoring, confirmation bias, availability, and affect heuristic. Other influential biases, such as framing effects, overconfidence, and hindsight bias, were not addressed in depth, though they also interact with emotion and merit further investigation.
2. **Variability of Study Designs:** The included literature spans a wide range of methodologies, from simulation studies and self-report surveys to systematic reviews and theoretical models. While this diversity enriches the analysis, it also introduces challenges in synthesizing findings across disparate formats and evidence levels [23-25].
3. **Indirect Measures of Outcomes:** Many studies rely on proxies (e.g., simulation performance, diagnostic accuracy in vignettes, or self-assessed EI levels) rather than direct patient-level outcomes like morbidity, mortality, or real-world diagnostic error rates [23], [16], [28].
4. **Potential for Publication Bias:** Studies showing positive effects of interventions like mindfulness or EI training may be more likely to be published, possibly overstating their effectiveness. Additionally, few studies report long-term follow-up data on the sustainability of these interventions' effects.
5. **Generalizability Constraints**: Most research was conducted in high-income countries and focused on physicians, particularly in acute care settings. Results may not fully translate to other clinical roles (e.g., allied health professionals) or under-resourced health systems.
6. **Evolving Nature of AI Tools:** The section on AI bias mitigation reflects tools available as of 2025. As these technologies evolve, new forms of bias or unforeseen human-AI interaction issues may emerge, requiring ongoing reassessment [1 - 6], [28].

7. **Screening Scope and Selection Process**: While the initial search returned over 14,000 results, the full review process applied strict inclusion criteria, and only a subset was examined in-depth. The narrowing process relied on title and abstract screening to exclude clearly irrelevant studies. As a result, some potentially relevant articles may have been inadvertently excluded before full-text review. This pragmatic approach prioritized depth over exhaustive breadth and was necessary to maintain feasibility within project constraints.
8. **Operational Definition Limitation:** The review did not standardize definitions of emotional states across studies (e.g., stress vs. burnout vs. frustration), limiting direct comparability. Many studies used self-report or proxy measures, introducing variability in emotion measurement.

Despite these limitations, the interdisciplinary synthesis offered in this review provides a valuable lens for understanding the emotional-cognitive interface in medicine and highlights actionable strategies to mitigate risk. This review did not conduct a formal risk of bias assessment of included studies, and not all initially identified articles were reviewed in full. Further research using standardized outcome measures, longitudinal designs, and culturally diverse samples will strengthen the evidence base and inform broader implementation. These limitations highlight the need for standardized emotion metrics, real-world outcome tracking, and broader representation in future studies.

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Distribution of Responsibilities for the Semester

Task	**Estimated Hours**	**Completion Status**	**Milestone**
Topic Selection and Research Question Refinement	5 hrs	✅ Completed	Project Pitch
Initial Literature Compilation (searching databases: PubMed, and Google Scholar)	15 hrs	✅ Completed	Weeks 1–2
Annotation and Thematic Coding of Selected Articles (N=35)	15 hrs	✅ Completed	Weeks 2–4
Literature Synthesis and Bias Categorization	10 hrs	✅ Completed	Week 4
Theory Mapping (Dual-Process, CLT, CRUM, Affective Neuroscience)	8 hrs	✅ Completed	Week 5
Drafting Literature Review Section	10 hrs	✅ Completed	Week 6
Results Section (categorizing emotional triggers, biases, and intervention findings)	11 hrs	✅ Completed	Week 7
Writing Discussion Section (implications, applications, theoretical insights)	7 hrs	✅ Completed	Week 8
Writing Limitations and Conclusion Sections	5 hrs	✅ Completed	Week 9
IEEE Formatting and Reference Management (Zotero/EndNote)	4 hrs	✅ Completed	Week 10
Peer Feedback and Revisions	0 hrs	- ----	Optional
Slide Preparation for Final Presentation	5 hrs	✅ Completed	Week 12
Final Edits and PDF Submission	5 hrs	✅ Completed	Week 12