Drawing the Line Between Efficiency and Care: Perceptions of AI Among Healthcare Workers

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1. Abstract

AI is highly praised as a route to increased efficiency and effectiveness in medicine, but its implementation is instead primarily driven by how clinicians secure accountability, professional self, and trust from their patients rather than an operation of technical effectiveness. This study explores how practitioners establish boundaries for appropriate AI use in patient care. This study drew on exploratory, semi-structured interviews that were written and transcribed with 22 South Florida active practitioners (age ≥18) across specialty, urgent-care, and dental practices, which included administrators, dentists, MDs, PhDs, nurse practitioners, and other specialists. We subsequently organized their perspectives using inductive thematic analysis informed by grounded theory techniques (open and axial coding), peer discussion, and reflexive journaling.

From this, four key themes emerged: (1) tension between efficiency and responsibility, (2) professional identity and moral judgment, (3) concerns about task automation versus job displacement, and (4) the need for transparency and supervision. Our central finding is a Boundary Reason Typology that systematically maps acceptable AI uses (scribing, templating, image pre-reads) to specific professional rationales including empathy preservation, workflow congruence, scope of practice, and human oversight requirements. With this in mind, we recommend that AI be framed as assistive, that human sign-off be necessitated, that readable reasons for doubt be surfaced, that interfaces be integrated into workflow, and that role-specific training be implemented that preserves professional identity. We hold that future research must broaden settings and stakeholders, that interview studies be supplemented with workflow monitoring and logs, and that interface and training paradigms that preserve clinician authority be tested with measurable efficiency increases.

Keywords: Artificial intelligence in healthcare, clinical decision-making, professional identity, patient trust, accountability, workflow integration, transparency, Human-in-the-loop oversight, professional autonomy, qualitative thematic analysis

2. Introduction

2.1 Background

Across various South Florida healthcare sites, staff express mixed views about the integration of AI in patient care. One chiropractor welcomed AI-driven scribing tools with the reasoning that documentation gives him “the worst headaches” when he is too busy. By contrast, a dental practice administrator said that their office “goes against” replacing their staff with AI because patients “need a one-on-one conversation” and authentic “human interaction.” These divergent views portray a broader pattern: personnel are neither categorically pro nor anti-AI.

Instead, they negotiate role boundaries that accept technological assistance while, at the same time, preserving a degree of professional judgement that allows them to have a measurable impact in the scope of AI in their respective institutions.

2.2 Literature Review

Through studies, surveys, and reviews, the threads that are strongest are that physicians are not “pro-AI” or “anti-AI” in the abstract, but selectively pro assistive technologies that alter administration but not human judgment. Scoping and integrative studies syntheses demonstrate acceptance depends upon usefulness, integration into workflow, education, and governance, but not upon AI per se (Lambert, 2023; Henzler, 2025; Hassan, 2024). Surveys and mixed-methods work confirm the same: physicians and nurses are happiest in documentation support, triage/prioritization, and information extraction, but least confident in those applications in which systems seem to displace decisions about therapy or diagnosis (Allen, 2024; Antes, 2021; Giavina-Bianchi, 2024). Professional standards reaffirm: minimizing administrative hassle is the American Medical Association’s highest-value near-term use case, specifically defined as assistive, not substitutive, AI (American Medical Association, 2025). Industry estimates report adoption clustering in assistive tooling with time savings and clerical relief, rather than full autonomous clinical decision-making (DemandSage, 2024) Drawing on qualitative dermatology interview work and subsequent synthesis, clinicians describe AI as a tool or assistant rather than a replacement, with some framing it as a “peer” for a second look, all while keeping human judgment central (Göndöcs & Dörfler, 2024). These threads, all together, constitute a tapestry that places adoption as a productivity gain calculus that preserves, but doesn’t obliterate, clinical agency (Lambert, 2023; Henzler, 2025; Hassan, 2024; Allen, 2024; Giavina-Bianchi, 2024; American Medical Association, 2025; DemandSage, 2024; Antes, 2021; Göndöcs & Dörfler, 2024). Questionnaires and policy guidance converge that interpretability, the ability to override recommendations, and clear accountability improve acceptability (Hassan, 2024; Almyranti, 2024; Australian Medical Association, 2023). Another set of convergences deals with trust: ethical accounts warn black-box systems erode informed consent, shared decision-making, and equitable liability if they fail (London, 2019; Grote & Berens, 2020). Policy norms cycle traceability, documentation, risk management, and human control requirements standards (Almyranti, 2024; Australian Medical Association, 2023). EU AI Regulation governance studies ascribe those aims in practical organizational duties of healthcare deployers (van Leeuwen, Doorn, & Gelderblom, 2025). The literature thereby redraws explainability and override as more than quality-assurance modules but as ethical checks for trust with patients and liability in clinicians (London, 2019; Grote & Berens, 2020; Almyranti, 2024; Australian Medical Association, 2023; van Leeuwen, Doorn, & Gelderblom, 2025; Allen, 2024; Hassan, 2024). "Patient as person" stories call forth humanist roots of medicine, presence, interpretation, empathy as the pathway into trust and healing (Verghese, 2008). Recent research with qualitative and quantitative approaches illustrate how AI assumes insulting professional identity as it gets inserted into clinical judgment, flipping over legitimacy, prestige, and what it is like to be an expert (Ackerhans, 2025; Rony, 2024). Job-design research connects adoption to psychosocial demand (autonomy, competence, relatedness) and chronicles the same tech empowering or disempowering based on how it re-mediates who decides/why of a task (Huo, 2025). Pragmatic accounts in mixed-method studies take the assumption that clinicians are happiest about making AI first when they get to decide whether and how, but not when, it is done unto them (Allen, 2024). The line inserts adoption into boundary work for identity maintenance: a fear that our research lays out and describes directly.

Acceptance and perceived risk systematically depend on professional role, location of care, and country infrastructure. Nursing is positive in attitude with exhortations as an adjunct to education, definition of scope, and governance (Wang, 2024; Alruwaili, 2024). Questionnaire surveys of whole hospital populations vary in knowledge and confidence with implications for differential education prerequisites as well as local leadership variables (Al-Qudimat, 2025; Henzler, 2025). Systematic reviews in hospital environments also involve organization readiness, interoperability, and culture as prerequisites for positive implementation (Lambert, 2023; Hassan, 2024). Discretionary control of AI is preferred by primary care clinicians, again linking acceptance with autonomy and accountability (Allen, 2024). Such variation betrays the same capacity to cross highly dissimilar boundary lines as a function of professional role (e.g., radiology, surgical, and reception desk personnel), workflow, and institution policy (Wang, 2024; Alruwaili, 2024; Al-Qudimat, 2025; Henzler, 2025; Lambert, 2023; Hassan, 2024; Allen, 2024).

Governance is moving towards "assistive + oversight" but operationalization is lagging behind. Cross-national policy declarations and professional positions converge in a human-in-the-loop assistive use model with monitoring, risk-based oversight, transparent records, and open disclosure (Almyranti, 2024; Australian Medical Association, 2023; American Medical Association, 2025). Regulatory analysis places emphasis on monitoring responsibilities, reporting of incidents, role-specific training, and audit trails (van Leeuwen, Doorn, & Gelderblom, 2025). Scoping and integrative reviews identify common enablers (training, stakeholder engagement, explainability, usability) and barriers (data quality, bias, workflow mismatch, unclear accountability) (Hassan, 2024; Henzler, 2025; Lambert, 2023). Experimental and scenario-based studies show that acceptability is enhanced when systems allow for overrides and norms of disclosure apply (Antes, 2021; Allen, 2024). But during this convergence, what "sufficient explainability" or "adequate oversight" entails, for a nurse vs. surgeon vs. administrator, is still too vague (Almyranti, 2024; van Leeuwen, Doorn, & Gelderblom, 2025; Hassan, 2024).

2.3 Boundary Reason Typology

Together, the literature and our interviews imply a boundary typology. Uniformly supported uses, scribing, templating, summarizing, image pre-reads, scheduling, map to workflow relief and efficiency (Lambert, 2023; American Medical Association, 2025; DemandSage, 2024; Hassan, 2024). The interaction roles reported in the dermatology literature, tool, assistant, and in some accounts a ‘peer’ for second-look comparison, map naturally onto our boundary reasons (Göndöcs & Dörfler, 2024): boundary-defining uses, autonomous diagnosis, unsupervised choice of treatment, engage moral agency, professional identity, and clarity of liability (Allen, 2024; Ackerhans, 2025; London, 2019; Grote & Berens, 2020). Within categories, acceptability is buttressed by explainability and ease of override (Hassan, 2024) and undercut by tools that eat into empathy or rapport with patients (Verghese, 2008; Grote & Berens, 2020). Role-specific patterns appear: radiology stresses double-checking and error avoidance; surgeons, autonomy; administrative staff, facilitation of communication and workflow continuity (Allen, 2024; Wang, 2024; Alruwaili, 2024; Al-Qudimat, 2025). Policy structures reinforce these intuitions by placing human oversight, documentation and disclosure demands in place (Almyranti, 2024; Australian Medical Association, 2023). Three gaps still remain, however, even in the presence of convergence. First, there is a why-mapping gap: the literature correctly reports what clinicians accept, but comparatively little research associates described acceptable use with the reasons clinicians provide that are role-specific (e.g., empathy, oversight, scope, accommodation to workflow). Second, there is an operationalization gap: policy demands “human in the loop” and “explainability,” but little, role-specific, information about how much oversight/explanation is sufficient in day-to-day practice is available in the literature. Third, there is a relational/identity gap: quantitative determinations of “trust” all too often ignore professional identity and patient rapport, while qualitative and ethical studies verify that they are preeminent fault lines (Ackerhans, 2025; Rony, 2024; Verghese, 2008; Grote & Berens, 2020). Our research bridges the gap by (1) building a Boundary Reason Typology that formally maps approved and limited activities onto clinicians’ listed reasons (scope of practice, workflow alignment, human override, empathy, efficiency) (Allen, 2024; Lambert, 2023), (2) segmenting by role and by location to highlight differences in boundary reasoning (van Leeuwen, Doorn, & Gelderblom, 2025), and (3) recasting explainability and override as moral reassurance, mechanisms that affirm identity and trust and inform governance design and training targets (Grote & Berens, 2020; Verghese, 2008).

2.4 Purpose of the Study

Through systematized interviewing of dentists, front office staff, office managers, pediatricians, nurses, chiropractors, as well as medical specialists, phenomenological research delves into the way through which healthcare providers set boundaries on the proper role of AI in patient care. The research documents statements from administrative staff, dental specialists, office managers, as well as physicians from multidisciplinary grounds, documenting the way through which various members of staff on the health providing team set various limits based on their particular tasks as well as values as professionals. As industry estimates suggest, many organizations report AI use and positive returns, for example an average of about $3.20 per $1 within roughly 14 months; understanding how staff set boundaries is integral to retaining both technological advantage and professional freedom (DemandSage, 2024). Building on Göndöcs & Dörfler's (2024) tool/assistant/peer roles and prediction–judgment distinction, our study extends these patterns beyond dermatology to multiple roles and settings, specifying role-specific boundary reasons that preserve accountability while realizing efficiency. What results demonstrate is complex balancing of technological expediency as well as human-centered care that characterizes the manner professionals themselves define AI integration into existing medical practice.

3. Methods

3.1 Research Design

We used an interpretivist orientation and inductive thematic analysis, informed by grounded theory techniques (open and axial coding) to examine how healthcare professionals define boundaries for artificial intelligence (AI) within patient care. We conducted 22 semi-structured interviews ranging from 20-60 minutes with practitioners across urgent-care, dental, and specialty practices in South Florida, including physicians, dentists, nurse practitioners, and administrators across March-June 2025. Interviews were audio-recorded, transcribed verbatim, and analyzed through grounded thematic coding, peer debriefing, and reflexive journaling to identify patterns in how clinicians balance technical assistance with human discretion.

We adopted an interpretivist orientation because our aim was to understand how clinicians construct meaning around AI within their local contexts and professional identities, rather than to estimate prevalence of attitudes. Interpretivist approaches are well suited to capturing situated sense-making and the social processes through which practice norms are negotiated (Pope & Mays, 2020). We used an inductive thematic analysis to allow patterns to emerge from participants' accounts while following best-practice guidance for identifying, reviewing, and naming themes directly from the data (Braun & Clarke, 2006, 2019). To strengthen analytic rigor, we incorporated grounded theory techniques, line-by-line open coding and axial coding, to move systematically from initial codes to higher-order categories and a mid-range conceptual model. This design choice is consistent with qualitative health research where the goal is to surface shared logics and role-specific differences in complex, evolving domains, and it aligns with accepted criteria for credibility, dependability, and confirmability through reflexivity, peer debriefing, and audit trails (Pope & Mays, 2020)

This design was informed by methodologies used in similar AI research, particularly (Göndöcs and Dörfler, 2024), who conducted semi-structured interviews with 17 dermatologists to explore expectations of AI in diagnosis through open-ended interviews and coding analysis. Our study extends this approach to a broader and more diverse group of healthcare professionals to capture a wider range of perspectives on AI integration. This approach aligns with best practices in qualitative health research and is underpinned by empirical findings on sample adequacy (Wutich, Beresford, & Bernard, 2024).

3.2 Participants & Recruitment

This study engaged 22 healthcare practitioners (age ≥18) working in South Florida, including MDs, dentists, nurse practitioners, administrators, and other clinical specialists across urgent-care, dental, and specialty settings. We used purposive, maximum-variation sampling across roles and settings. Participation was voluntary, and all participants were informed that no identifying information would be collected or reported. We did not record personal identifiers; only role and setting were captured in aggregate.

We visited urgent-care, dental, and specialty practices in Miami-Dade and Broward Counties during routine business hours and invited clinicians and staff to participate. Eligibility criteria were: (i) actively practicing in healthcare in South Florida, (ii) age ≥18, and (iii) ability to complete a 20-60 minute semi-structured interview in English. Individuals were excluded if they were not currently practicing or were unavailable within the study window. Interested staff received a brief study information script, provided verbal consent, and were interviewed on-site or scheduled at a convenient time; no incentives were offered. We obtained verbal permission from on-duty managers before approaching staff and avoided patient-care interruptions. The most common reason for non-participation was time constraints (patient load, staffing), and recruitment continued until no new codes emerged in the final three interviews (n=22).

Our sample size of 22 interviews is methodologically defensible. Prior work indicates that theme saturation often occurs after approximately nine interviews, with deeper meaning saturation emerging by 16-24 interviews (Wutich, Beresford, & Bernard, 2024; Hennink, Kaiser, & Marconi, 2017). In our study, no new codes emerged in the final three interviews, indicating that both code and meaning saturation were achieved, supporting the adequacy of the sample for capturing diverse perspectives across roles.

3.3 Ethical Considerations

This project was conducted as an educational, quality-improvement activity with voluntary, anonymized participation. No IRB determination was sought due to the study not meeting the criteria for human subjects research as defined by 45 CFR 46; this is a limitation, and future work should obtain formal review. Participants provided verbal informed consent. No PHI was collected; audio and transcripts were de-identified and stored on encrypted, access-controlled drives.

3.4 Data Collection

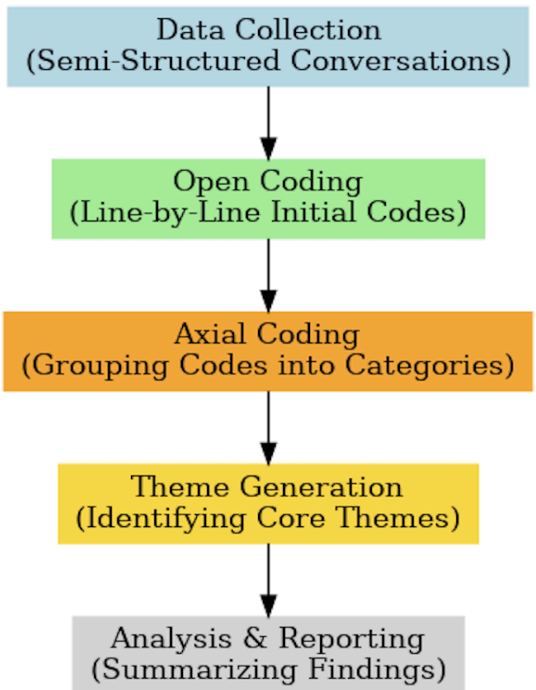
Exploratory, semi-structured interviews were conducted to examine clinicians' perceptions of AI in patient care. Each conversation lasted approximately 20-60 minutes and was held in person. Broad, open-ended prompts guided the discussions, including topics such as perceived benefits and limitations of AI, boundaries for clinical use, and ethical concerns regarding patient interaction and trust. Notes were taken in concurrence with transcripts that were verified in accordance with said notes to document key insights. This was then used to refine the study's analytical framework and identify recurring concepts, though they were framed as expert consultations rather than formal human-subjects interviews. No identifiable or sensitive information was recorded at any stage. Transcripts were double checked against recordings in order to confirm accurate data. In addition to this, a non-partisan stance was maintained via using a common interview guide while allowing follow-ups to pursue emergent topics to ensure the reliability of data that was collected. No new codes emerged in the final 3 interviews.

3.5 Data Analysis

Reported perspectives were used to identify illustrative themes that aligned with or challenged existing literature. Intercoder reliability was maintained through peer checking, resolving discrepancies via discussion. Themes were compared to patterns identified in the existing literature, while also noting ideas that arose organically in exploratory conversations. NVivo Version 14 was utilized in order to assist in inductive thematic coding to ensure the utmost accuracy.

The interview data were analyzed via an inductive thematic approach informed by grounded theory techniques. First, open coding was applied by reading each transcript line-by-line and labeling distinct ideas with short, descriptive codes such as “efficiency,” “human oversight,” “loss of human touch,” and “trust in AI.” Next, axial coding was conducted to group related open codes into broader categories by identifying connections and patterns among them. For example, codes related to “efficiency,” “workflow relief,” and “time-saving tools” were clustered under the category Efficiency and Workflow Enhancement, while codes emphasizing “supervision,” “human responsibility,” and “ethical guardrails” were combined under Human Oversight and Responsibility. Finally, these categories were synthesized into three overarching opinion groups, Enthusiastic Adopters, Cautious Supporters, and Skeptical or Ambivalent Respondents, which structured the presentation of the results and aligned with participants’ perspectives as described in the following section 4. Analysis followed an iterative, grounded approach. We tracked both code saturation and meaning saturation, using Hennink et al.’s (2017) framework to ensure not only the emergence of themes but a comprehensive understanding of their nuances.

Coding Process (Figure 1)



3.6 Boundary Reason Typology (Figure 2)

The following typology presents illustrative examples from exploratory conversations with healthcare professionals. These examples are organized thematically to highlight recurring ideas that practitioners shared about AI boundaries in their work.

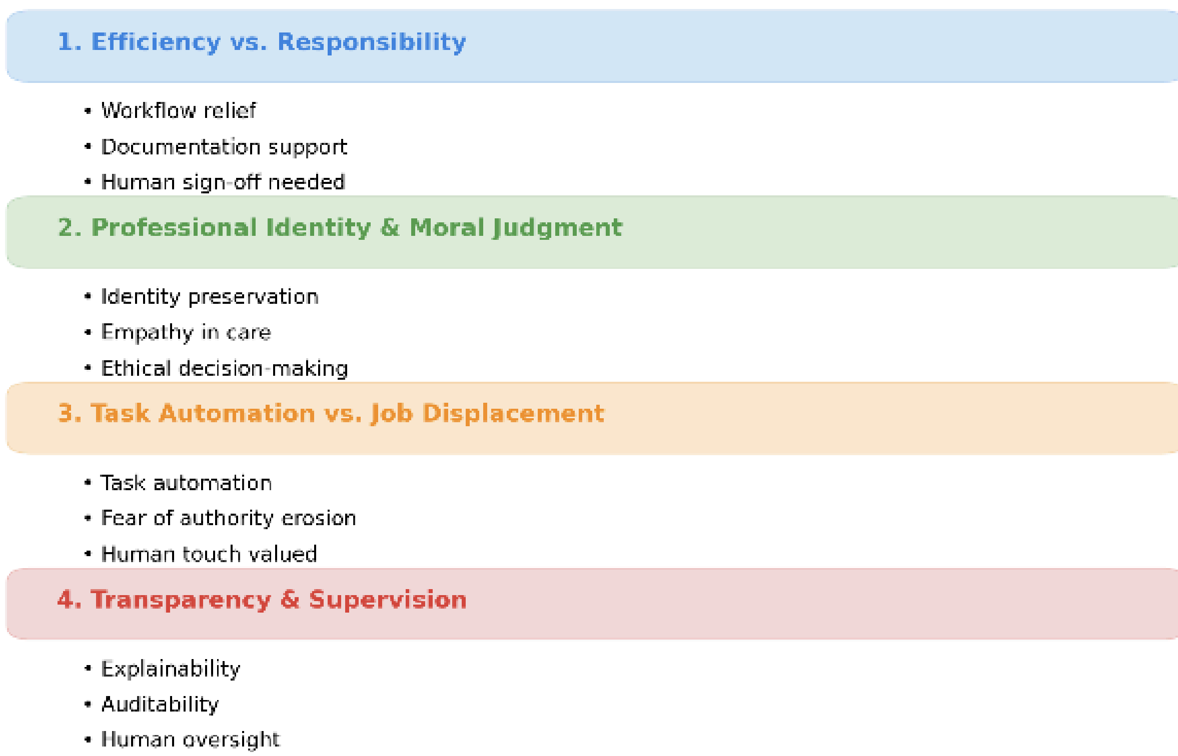
Participant	Role	Authorized AI Use	Main Reason for Boundary	Concern Area

1	Dentist	Diagnostics	Sentimental attachment	Empathy
2	Administrator (Dental Office)	Administrative tasks	Effectiveness	Workflow
3	ER Physician	Emergency pattern identification	Ethical framework lacking	Ethics
4	Administrator (Urgent Care)	Scheduling	Requires human review	Control
5	Chiropractor	Documentation	Absence of emotional intelligence	Empathy
6	Administrator (Urgent Care)	Templating health records	Security threat	Data Privacy

7	Pediatrician	Charting, patient education	Integration cost	Workflow
8	Administrator (Urgent Care)	Administrative tasks	At institution’s discretion	Governance
9	Front Office Staff	Assisting doctor	Role definition	Scope of Practice
10	Dentist	Rare usage	Human-oriented philosophy	Empathy
11	Gastroenterologist	Colonoscopy support	Visual enhancement	Clinical Usefulness
12	Surgeon	None in surgery	Preserves autonomy	Autonomy
13	Dentist	Diagnostic instrument	Doctor confirmation required	Policy

14	Receptionist	Scheduling	Minimal reliance	Trust
15	Dental Administrator	Automatic invoicing	Human interaction required	Empathy
16	Orthodontist	Imaging support	Enhance but not replace	Accuracy
17	Nurse	Vitals logging	Speed not a substitute for care	Time Constraints
18	Radiologist	Image triage	Requires manual double-checking	Hazard Avoidance
19	Administrator (Urgent Care)	Admin, templating	Needs certified training	Education
20	Medical Assistant	Note transcription	Cannot replace human description	Documentation

21	Front Desk Administrator	Call routing	Requires human communication	Communication
22	Family Practice MD	Lab test notification	AI assists but final decision by doctor	Final Decision



This classification reveals how career function, philosophical reasoning, and operational considerations shape boundaries for AI use in medical settings.

3.7 Rigor and Reflexivity

Methodological rigor was maintained through peer debriefing and reflexive journaling during data collection and analysis. Reflexivity was particularly important due to the interviewer’s proximity to the healthcare field. Efforts were made to bracket biases and prioritize participant voice over theoretical interpretation. Notes from conversations were reviewed to ensure consistency and to avoid overinterpreting anecdotal perspectives. This transparent approach supports the validity and transferability of findings, accurately reflecting healthcare workers' nuanced beliefs about AI in patient care. Maintaining reflexivity, engaging in peer debriefing, and deliberately tracking saturation milestones align with emergent recommendations for transparency in sample adequacy and saturation evidence (Wutich et al., 2024; Hennink et al., 2017). De-identified excerpts are available on request; full transcripts not shared to protect anonymity.

4. Results

4.1 Overview of Opinion Groups

Following are the results of the semi-structured interviews of 22 healthcare respondents, labeled as Participant 1-22 to maintain confidentiality. Results have been coded into three opinion groups on thematic coding-based grounds: Enthusiastic Adopters, Cautious Supporters, and Skeptical/Ambivalent. They are ordered within each group by interview date. Quotes reflect the respondents' own words and are accompanied by their position on AI implementation.

4.2 Enthusiastic Adopters

These participants appreciated AI for its potential to increase efficiency, reduce workload, and facilitate clinical work, provided there was adequate monitoring.

Participant 1 (Dentist): "No one can replace a human touch with another human…"

Participant 2 (Administrator): "Anything and everything I don't have to do…"

Participant 3 (ER Doctor): “Artificial intelligence without ethics is a challenge…”

Participant 4 (Administrator, Urgent Care Center): “Always monitored. Yes, all.”

Participant 5 (Chiropractor): “AI will not have the will that I have…”

Participant 6 (Administrator, Urgent Care Center): “It has to be monitored… it has access to all clinical…”

Participant 7 (Pediatrician): “The problem lies in compatibility with our programs…”

4.3 Cautious Supporters

These respondents valued AI’s contributions but stressed the need for strict control, ongoing dialogue, and preservation of emotional connection in patient care.

Participant 8 (Administrator, Urgent Care): “If the corporate does it, I’m fine…”

Participant 9 (Front Office Staff): “No patient care, but assisting the doctor is OK.”

Participant 10 (Dentist): “We want people treating people.”

Participant 11 (Gastroenterologist): “It will assist in diagnosing polyps.”

Participant 12 (Surgeon): “Is AI going to be down here to say, okay… what I was trying…”

Participant 13 (Dentist): “I wouldn’t trust that 100%.”

4.4 Skeptical or Ambivalent Respondents

These participants expressed concern about AI replacing professional judgment and diminishing patient interaction.

Participant 14 (Receptionist): “You don’t want it ringing the wrong phone…”

Participant 15 (Dental Administrator): “Some still prefer to talk with an individual…”

Participant 16 (Orthodontist): “If we save time but screen results, that’s fine.”

Participant 17 (Nurse): “Speed isn’t necessarily best where patients are concerned.”

Participant 18 (Radiologist): “You still have to double-check every AI diagnosis.”

Participant 19 (Front Office Staff): “I want someone qualified to train that AI.”

Participant 20 (Medical Assistant): “It overlooks the finer details that patients talk about.”

Participant 21 (Front Desk Administrator): “It will not calm a disturbed patient down.”

Participant 22 (Family Practice MD): “Good for flagging, but I decide what’s urgent.”

4.5 Concluding Thoughts

All respondents recognized a potential role for AI in facilitating healthcare workflows and diagnostics, while agreeing that human agency remains critical. Optimistic proponents emphasized efficiency gains, cautious supporters valued ethical safeguards and autonomy, and skeptical respondents prioritized maintaining human touch and judgment. This thematic breakdown illustrates the richness and diversity of professional attitudes rather than clustering them into a single stance toward AI.

5. Discussion

5.1 Overview of Themes

By synthesizing national surveys, policy reports, and published literature on AI in healthcare, supplemented with our exploratory practitioner perspectives, we illuminate the ethical and identity-laden logic behind these boundaries. Here we discuss four main themes that we deem to be worthy of elaboration: Efficiency vs. Responsibility, Professional Identity & Moral Judgement, Task Automation vs. Job Loss, and finally Transparency & Supervision. Each of these tie in with existing literature and is woven in throughout each of the respective themes.

5.2 Efficiency vs. Responsibility

Regarding the first theme of Efficiency versus Responsibility — in which we observed a general trend for the request of clinical relief in the form of real-time documentation. Yet simultaneously, there was still a demand for a human sign off on diagnosis. This can be seen in two different aspects in real time, with two respective doctors in Miami, one already utilizing AI for scribing purposes, while the other requests an AI tool to assist with notetaking as a whole: exemplifying the upscale demand for efficiency in an already busy workplace. This echoes the post-COVID "support-not-replace" stance (Almyranti, 2024) but sharpens it: our participants articulated responsibility diffusion as the key fear, meaning that one would likely aim to blame the person who coded said program. This stance was observed in each position we interviewed: administrative managers to PhDs. This matches findings from a peer-reviewed study (Allen et al. 2024), which argues that when AI encroaches on diagnostic authority, clinicians perceive a threat to their moral legitimacy. Consistent with qualitative findings among 17 dermatologists, clinicians prefer AI in assistive roles while retaining final responsibility for diagnosis and communication, not from job-fear but from professional duty (Göndöcs & Dörfler, 2024). These concurrent findings in conjunction with already existing literature imply that accountability risks eroding clinicians' moral authority, which subsequently has the effect of eroding patient trust: reflecting our theme of Efficiency versus Responsibility to a large extent. These patterns align with a prediction–judgment architecture (Göndöcs & Dörfler, 2024): meaning that AI offers a prediction; the clinician renders the judgment and communicates it, preserving accountable authorship of care.

5.3 Professional Identity & Moral Judgement

A second major theme that emerged was the importance of human connection in patient care, which clinicians felt must remain beyond the reach of AI. This was echoed by a doctor at a private dental practice in Davie, and the exact same message was brought forth by another doctor in Plantation. The general consensus does indeed bring forth a philosophical dilemma: how can one implement AI while also mitigating its effects on the emotional aspects of patient care. Extant literature (Verghese, 2008; Grote & Berens, 2020) stresses this importance as well. However, prior quantitative work often measured comfort or trust, but seldom linked AI adoption to identity work (Ackerhans 2025). Our qualitative evidence fills that gap: the line is drawn where AI threatens clinicians' self-definition as ethical agents. This suggests training must address identity preservation: not just upskilling. It also reframes the aforementioned AI ethics debate: meaning that the question is not merely can AI be safe but can AI leave room for human dignity. Qualitative work likewise reports a preference for AI as tool/assistant/peer colleague: all modes that preserve clinical authority (Göndöcs & Dörfler, 2024). One physician suggested future systems might convincingly simulate empathic behaviors, a claim that warrants targeted study before practice implications are drawn.

5.4 Task Automation vs. Job Loss

Something that we noticed across all the various roles that we examined, was that participants distinguished between task automation and job loss. Administrative staff tended to welcome automation in scheduling, billing, and documentation, yet at the same time worried about both front-desk and doctorate roles losing the human touch that calms anxious or upset patients. Clinicians, on the other hand, generally accepted AI for templating, scribing, and image pre-reads, while drawing a hard line at autonomous diagnosis and procedure decisions, which they linked to moral agency and professional identity and having a human supervisor. A general theme that recurred in this sector was that participants expressed that a patient talking to a robot/AI would not have the same effect as communicating with an actual human. Thus, several interviewees framed job risk as less about headcount and more about erosion of authority, responsibility diffusion, and the loss of patient connection; this was especially the main grievance of more family-oriented or close-knit practices. Concern about replacement varies by role and seniority, which suggests that perceptions of risk are tied to where AI touches professional judgment versus routine throughput. These patterns align with our Boundary Reason Typology (Figure 2) and with external evidence: national-level data indicate physicians see AI's primary near-term value in reducing administrative burdens and documentation load, not in replacing clinical judgment (American Medical Association, 2025). Cross-country professional surveys likewise expect AI to transform care while keeping physicians central, with no expectation that AI will replace most physicians (Almyranti, 2024).

5.5 Transparency & Supervision

The final recurring theme that we investigated was the prevalence of transparency that was expressed. This concurs with another philosophical debate that yearns to be addressed: especially that of AI being responsible. Throughout several of those we conducted interviews on, they all agreed upon the basis that no matter what, the use of AI should be transparent. A peer-reviewed study (London, 2019) found that artificial intelligence must have transparency as an ethical requirement in order to be adopted in a clinical setting. Yet another study (Grote & Berens, 2020) argued that opaque systems threaten informed consent and shared decision-making: upholding that same ethical debate. In addition to this, there were concerns with AI accessing databases of personal information of patients, with participants (those from all fields we investigated) extensively worrying about financial information. Participants favored design transparency, auditability, and easy overrides — not only for error-catching but for moral reassurance. This dovetails with ethical arguments about explainability and consent (London, 2019; Grote & Berens, 2020) and with human-oversight obligations under the EU AI Act analyses (van Leeuwen et al., 2025). Clinicians also stressed scientific explainability (who built it, how it was validated, how it learns) and noted that trust accumulates via performance over time (Göndöcs & Dörfler, 2024).

6. Implications

6.1 Policy and Training Implications

Our findings carry significant and applicable implications for policy, while also shedding light on how AI should be trained in the field across urgent-care, dental, and specialty settings. Across interviews, participants drew a clear line between efficiency-enhancing tools, such as scribing or templating systems, and autonomous decision-making in diagnosis or treatment. This suggests that programs such as Large-Language Models (LLMs) and other supplemental tools must mandate human review of AI outputs, particularly in clinical decision-making contexts; this would be done in order to preserve accountability, which participants associated with reduced anxiety for patients and staff. By structuring AI use as a supplemental tool rather than replacing it outright, institutions can ensure that moral authority remains with human practitioners while also surely increasing efficiency across all aspects. The philosophical aspect of AI stresses great importance within this field and others;

showing the paving of demand in a way that still upholds human contact to a measurable extent.

6.2 Accountability and Ethical Oversight

In addition to this general consistency, participants also emphasized the importance that accountability has to be maintained if AI was to be integrated. There is indeed a valid concern about diffusion of responsibility, where blame could shift from clinicians to technology developers. Our findings demonstrate a need in the industry and others alike that there needs to be an explicit clearly delineated responsibility, while also incorporating ethical review in the process itself. When these safeguards are installed, our participants expressed more comfortability in adopting AI into their specific workplace: showing that as AI is kept ethical with restrictions in and of itself with supervision — which again ties back to the ethical and philosophical concerns that seem to repeat themselves over and over again.

6.3 Role Redesign over Staff Reduction

Organizations should treat AI deployment as role redesign, not staff reduction. Implementation plans should seek to specify which tasks are automated, which remain clinician-owned, and how saved time is reinvested in direct patient care. Clear supervision policies that couple both override systems and plain-language disclosures to staff and patients can reduce perceived replacement risk by reaffirming human decision rights. Training should include scripts for discussing AI with patients, plus role-specific upskilling that preserves professional identity. On a similar note, leadership should monitor perceived displacement over time, for example brief pulse surveys tied to each rollout, and pair automation with visible investments in staff growth, cross-training, and new career pathways. Positioning AI as a tool that elevates human work, rather than as something that replaces humans altogether, aligns adoption with the ethical and relational priorities expressed by participants.

6.4 Transparency and Moral Reassurance

Continuing on the common notion of maintaining transparency, interviewees consistently preferred AI tools that offered transparent reasoning processes and easily traceable decision paths. Systems should be designed to allow clinicians to see how an output was generated and to override it without difficulty. The preferences that we uncovered suggest that AI development in healthcare should prioritize features that foster moral reassurance, not only statistical confidence, thereby addressing both practical and ethical comfort for end-users. Our relevant findings point to a need for role-specific AI training programs that go beyond technical operation. That data adheres to the notion that training revolving around the integration of AI should include strategies for maintaining human connection in care, recognizing when AI use might threaten professional identity, and knowing exactly when to apply ethical judgment in technology-assisted contexts. By incorporating these elements, training can prepare clinicians and staff to integrate AI within their workplace while avoiding the central issue of compromising the values central to their practice. In the future, as some specialists suggested, as AI gets more advanced, it will be able to adopt such empathic human natures, something that some of our specialized participants in both Miami and Broward counties echoed as well. But for now, our findings provide significance to the healthcare community and beyond, as institutions and others can analyze our data and apply it to their case, since these views were shared across a range of roles and ages in our sample.

6.5 Recommendations for Future Research

Future literature and works should expand sampling across regions and care settings and also include other roles. Mixed-methods designs that pair interviews with workflow observations and audit logs would also help to shed light. Longitudinal studies can track shifts in identity, moral agency, and trust as capabilities and policies change. In addition to this, trialist studies can further expand upon knowledge of triage in relation to AI. Including perspectives from patients and caregivers will further clarify how AI and patient relationships could play out in the future. By also including aforementioned perspectives, institutions looking to integrate AI into their system, whether it be on an administrative level or a more extensive role, can reference an even more accurate dataset that can sway their decision.

7. Conclusion

7.1 Summary of Findings

Guided by an interpretivist and phenomenological lens, this paper synthesizes existing surveys, reports, and literature on AI in healthcare, along with notable and valuable practitioner perspectives, to show that boundaries are drawn less by technical capacity and more by how clinicians preserve responsibility, identity, and trust in care. Participants welcomed assistance that reduces documentation load and flags information, while simultaneously reserving diagnosis and treatment decisions for human judgment. Transparency and supervision emerged as ethical safeguards, not only as quality controls, and patient rapport remained a non-negotiable locus of human work.

7.2 Boundary Reason Typology

The Boundary Reason Typology in Figure 2 makes these logics visible across roles by linking acceptable uses to underlying rationales such as empathy, oversight, workflow fit, and scope of practice. This analysis, produced through grounded thematic coding in NVivo Version 14 with peer review and reflexive journaling, clarifies why acceptance concentrates on templating, transcription, and image pre-reads, and why resistance intensifies as AI nears core clinical judgment. The typology also explains role-specific variations in perceived job risk, which centered on the repetitive concern in the form of erosion of authority and human connection rather than headcount alone.

7.3 Practical Applications

Taken together, these findings suggest practical design and deployment lessons. Position AI as assistive, require human sign-off for clinical decisions, surface readable rationales and uncertainty, and provide role-specific training that protects professional identity while improving workflow. Finally, communicate openly with patients about when AI is in use and how human oversight is maintained throughout all facets and processes.

7.4 Limitations and Future Research

Due to the fact that our sample is purposive and region-specific, the contribution is transferability rather than statistical generalization. Voluntary participation bias also represents a limitation. Healthcare professionals who chose to participate may have held stronger opinions about AI, positive or negative, compared to those who would decline. Even though constraints and patient load were the most commonly cited reasons for non-participation, self-selection could have influenced our sample toward individuals with more definitive views on AI implementation. Our data collection occurred during a specific period (March-June 2025) and represents a single time-point snapshot of attitudes that may be rapidly evolving as AI capabilities advance and healthcare policies develop exponentially: especially over the next few years.

Expanding upon this notion, the absence of patient perspectives is also a limitation. Our study does exclusively look at clinicians and how they view AI. However, patients are the real recipients of AI-Assisted care. Patient views on AI transparency, comfort with AI involvement in their care, preferences for human interaction, and expectations for disclosure may differ from professionals. Future work should expand upon sampling across regions and care settings, include patient and caregiver perspectives, and employ mixed-methods designs that pair interviews with workflow observations and audit logs. Longitudinal studies should track how identity, moral agency, and trust evolve as AI capabilities and policies change, while experimental studies should test interface features and training models that sustain clinician authority while delivering measurable efficiency gains.

8. Appendices

8.1 Appendix A: Coding Framework

Theme 1: Efficiency and Workflow Optimization

Definition: AI tools that streamline documentation, data retrieval, and routine tasks without replacing human decision-making.

Codes: Scribe support, templating, pre-reading imaging, automated scheduling, chart summaries, EHR compatibility/integration, triage/prioritization, information extraction.

Theme 2: Human Judgment and Decision-Making

Definition: Clinicians reserving final judgment and critical decisions for human expertise, regardless of AI recommendations.

Codes: Human override, final sign-off, skepticism of automated diagnoses, reliance on clinical experience, scope-of-practice boundaries, liability clarity.

Theme 3: Transparency and Ethical Safeguards

Definition: The need for explainability, traceability, and human oversight in AI-supported processes to maintain accountability.

Codes: Explainability, readable alerts, system transparency, audit trails, accountability structures, patient disclosure, data security/privacy, access controls.

Theme 4: Patient Rapport and Professional Identity

Definition: Preservation of clinician-patient relationships and professional autonomy as central to trust and quality care.

Codes: Human touch, empathy, conversational nuance, resistance to full automation, role identity preservation, authority/role erosion, autonomy preservation, perceived replacement risk.

8.2 Appendix B: Interview Guides

Administrative Questionnaire:

1. Does your office currently utilize Artificial Intelligence?
2. Do you have any insights on pros or cons that you've heard or discussed regarding involving AI in healthcare?
3. What role do you see AI playing in the healthcare industry in the future?

4. Does your institution currently use AI, and if so how much would you say it assists you on a scale from one to 10, and in what particular way?
5. If AI were to be adopted in your workplace, what kinds of tasks would you like it to assist with? For example: An automated scheduler tool, handling calls, etc…
6. When you hear, “AI in healthcare,” what comes to your mind?
7. Are there any things that you wouldn’t trust AI to do?

8.3 Appendix C: Specialist Questionnaire

1. Does your office currently utilize Artificial Intelligence?

2. Do you have any insights on pros/cons that you’ve heard or discussed regarding AI in healthcare?

3. What role do you see AI playing in the healthcare industry in the future?

4. In the future, do you genuinely think AI will play a beneficial role in potentially saving lives?

5. What is your personal opinion on how AI might help or interfere with patient care?

6. When you hear “AI in healthcare,” what comes to your mind?

7. How do you usually learn new technology at work?

8. Would you feel confident adapting to new technologies?

9. Do you think AI could ever fully replace more specialized roles, such as surgeons and orthodontists?

10. What part of your job do you feel takes the most time or causes the most frustration? Do you think AI could help?

11. On a scale of 1 to 10, how concerned would you be about AI replacing jobs in healthcare?

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