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Recalibrating AI in clinical decision-making: a process view of human–AI engagement in healthcare

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ABSTRACT

This study examines how clinicians continuously recalibrate when, how, and to what extent artificial intelligence (AI) shapes clinical decision-making, moving beyond static adoption and resistance models that treat engagement as a stable outcome. Based on 29 interviews across diverse clinical roles, our analysis indicates that clinicians do not hold stable positions of adoption or resistance. Instead, they enact five recurring decision orientations in practice: withdrawn, concealed, selective, cautious, and routine, through which they adjust the extent, visibility, and authority of AI in clinical judgement. These orientations reflect distinct decision logics grounded in situational assessments of risk, responsibility, and clinical context, and clinicians may shift between them as conditions change. By theorising AI engagement as an ongoing process of decision calibration rather than a one-time acceptance decision, this study offers a process-oriented explanation of human–AI engagement and outlines implications for the design, implementation, and governance of clinically accountable AI.

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Artificial intelligence; human–AI engagement; decision calibration; decision orientations; clinical decision-making

1. Introduction

Artificial intelligence (AI) is increasingly integrated into healthcare, supporting diagnosis, clinical decision-making, risk prediction, documentation, and workflow coordination (Topol, 2019). Unlike earlier clinical information systems, many AI tools are rapidly evolving, partially opaque, and often deployed in advance of fully stabilised governance arrangements, clinical standards, or professional norms. Clinicians therefore must actively judge whether, when, and how AI should be involved in clinical decision-making, rather than simply follow fixed protocols (Liao et al., 2022; Sokol et al., 2025).

Existing research typically explains clinicians' engagement with AI through adoption or resistance, often conceptualised as general orientations towards technology use (e.g. Davis, 1989; Lapointe & Rivard, 2005; Venkatesh et al., 2003). While these works identify important drivers and barriers, they primarily focus on overall patterns of technology use and offer limited insight into how AI is navigated in everyday clinical work. In practice, decisions are made under conditions of uncertainty, time pressure, and professional accountability (Hassan et al., 2024; Vaid et al., 2023; Younas & Khanum, 2024). As a result, the same clinician may rely on AI in one situation, scrutinise it in another, or disengage when concerns about responsibility or perceived risk become salient (Tyskbo & Nygren, 2024).

While adoption and resistance models provide valuable insights into technology use, they offer limited explanations for these within-person, reversible shifts in engagement at the level of specific decisions. Although prior research has examined more dynamic aspects of technology use, including emotional and post-adoption responses (Beaudry & Pinsonneault, 2010), less attention has been given to how professionals actively regulate AI involvement across individual decision situations. In high-stakes clinical settings, clinicians do not occupy fixed positions as adopters or resistors. Instead, they dynamically recalibrate AI involvement in response to situational variations in risk, responsibility, and accountability. This suggests the need to complement existing perspectives with a decision-level understanding of how AI is integrated into clinical work.

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To address this gap, we shift the analytical focus from adoption outcomes to AI engagement as situated decision-making. Rather than replacing adoption and resistance perspectives, this study complements them by focusing on how AI involvement is dynamically configured within individual clinical decisions. Drawing on clinician interviews, we examine how clinicians recalibrate AI involvement across situations by adjusting its extent (how much it is used), visibility (how explicitly it is acknowledged), and authority (how much weight it carries). We theorise recurring decision orientations that capture how this calibration is enacted in practice. Specifically, we introduce decision orientations as a process-based mechanism explaining how AI engagement evolves across clinical situations. Accordingly, we ask:

RQ: How do clinicians dynamically calibrate AI involvement across clinical situations?

The remainder of the paper presents the theoretical background, methodology, findings, discussion, and conclusion.

2. Theoretical background

This section reviews dominant perspectives on AI adoption and resistance in healthcare and explains why they offer limited insight into how clinicians engage with AI in everyday clinical decision-making. It then introduces a process-oriented lens that foregrounds decision orientations as a way of theorising how clinicians dynamically calibrate AI involvement in practice.

2.1. Limitations of adoption and resistance perspectives in healthcare AI

Research on healthcare AI has largely drawn on technology adoption and resistance theories, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Venkatesh et al., 2003), as well as resistance-oriented frameworks examining opposition to new systems (Lapointe & Rivard, 2005). These perspectives have identified key determinants of technology use, such as perceived usefulness, ease of use, and social influence. Subsequent research has also extended these perspectives by examining how emotions, adaptation, and post-adoption behaviours shape technology use over time (Beaudry & Pinsonneault, 2010; Bhattacherjee, 2001).

However, these models generally focus on explaining the overall patterns of technology adoption and use, providing limited insight into how engagement varies within the same individual across clinical situations and tasks (Bhattacherjee, 2001; Lapointe & Rivard, 2005). In practice, clinicians may rely on AI in one context, consult it cautiously in another, or disengage when perceived risk or accountability concerns become salient. Forms of engagements such as selective use, concealed reliance, or temporary withdrawal are difficult to capture when technology use is examined primarily through aggregate usage patterns or general orientations towards a technology rather than through situated decision-making.

Post-adoption theories acknowledge that technology use evolves through processes such as adaptation, appropriation, or resistance-in-use (Bhattacherjee, 2001; DeSanctis & Poole, 1994). However, they focus primarily on trajectories of use over time rather than on how individuals dynamically regulate technology involvement at the level of specific decisions. As a result, comparatively less attention has been given to how professionals actively calibrate the role of AI within individual decision situations, particularly in contexts characterised by high accountability and patient risk. Whereas adoption and resistance models explain overall usage patterns at the system level, our focus is on how clinicians regulate AI involvement at the decision level.

Recent qualitative studies have explored clinicians' experiences and concerns regarding AI (Amann et al., 2023; Fazakarley et al., 2023; Moldt et al., 2025). While this work provides valuable contextual insights, it often focuses on implementation or general attitudes rather than theorising how clinicians dynamically regulate AI involvement in everyday decision-making. Addressing this gap requires examining AI engagement as situated decision-making, where clinicians continuously calibrate AI involvement across clinical tasks and contexts. In this study, we address this gap by theorising decision

orientations as recurrent patterns through which clinicians calibrate AI involvement across clinical decision situations.

2.2. From adoption outcomes to decision orientations

Addressing these limitations requires shifting the analytical focus from adoption as an outcome to AI engagement as a situated decision-making practice. Rather than asking whether clinicians adopt or resist AI, this study examines how clinicians decide whether, when, and how AI should shape clinical decision-making. From this perspective, AI engagement is an ongoing, context-sensitive process in which clinicians continuously evaluate how AI should be positioned within their decision-making environment.

Clinical decision-making in healthcare is inherently complex and shaped by contextual factors such as task demands, perceived risk, and professional accountability. These characteristics make AI use both particularly risky and highly consequential in healthcare (Bardhan et al., 2025; Topol, 2019), as diagnostic and treatment decisions involve high levels of uncertainty and significant consequences for patient outcomes. We focus on these factors because they represent core conditions under which clinical decisions are evaluated, capturing task-related complexity (task demands), outcome uncertainty (risk), and professional responsibility (accountability), which jointly shape how clinicians assess the appropriateness of AI involvement. This highlights the importance of evaluating how AI involvement is configured within clinical decision-making. In such environments, clinicians must assess whether AI involvement is appropriate in relation to task complexity, the risks associated with AI-generated recommendations, and their responsibility for the final decision (Glikson & Woolley, 2020; Longoni et al., 2019).

This process-oriented view aligns with practice-based perspectives in information systems research, which emphasise that technology use is enacted through ongoing adjustment rather than determined by prior intentions or fixed protocols (Leonardi, 2011; Orlikowski, 2000). It also resonates with research on information technology implementation, which emphasises that technology use evolves through stages of adaptation, routinisation, and ongoing adjustment within organisational contexts rather than occurring as a single adoption decision (Cooper & Zmud, 1990). Clinical decision-making involves professional judgement, and AI involvement is shaped by situational evaluations of responsibility and uncertainty (Elwyn et al., 2012).

Research on human – AI collaboration further suggests that professionals actively regulate the role of AI systems within their work rather than delegating decisions entirely to automated systems (Jarrahi, 2018; Seeber et al., 2020). These perspectives highlight that AI involvement is not fixed but continuously adjusted within professional practice as clinicians vary its role across different decision contexts.

Building on this perspective, our analysis identifies three interrelated dimensions through which clinicians calibrate AI involvement: extent (the degree of reliance on AI), visibility (the extent to which AI use is made explicit within clinical workflows), and authority (the influence of AI outputs on clinical judgement). These dimensions emerged inductively from clinician interviews and are consistent with prior work on human – AI collaboration (e.g. Bussone et al., 2015; Jarrahi, 2018). Together, they capture how clinicians translate situational assessments of task demands, perceived risk, and accountability into concrete configurations of AI involvement, shaping how control and responsibility are distributed in practice.

These configurations give rise to recurring patterns of AI use, which we conceptualise as decision orientations. Decision orientations represent recurrent patterns through which clinicians organise the extent, visibility, and authority of AI involvement in response to situational conditions. They are not user types but patterns of situated action through which clinicians enact professional judgement under varying accountability demands. These orientations include routine, cautious, selective, concealed, and withdrawn engagement, each reflecting a distinct configuration of the three dimensions.

Decision orientations illustrate how patterns of engagement may reflect both adoption and resistance as dynamic, situational stances enacted across tasks and over time. By foregrounding ongoing decision calibration, this perspective reframes AI engagement as a dynamic process rather than a one-time acceptance decision and provides a theoretical lens for understanding how clinicians maintain professional responsibility while integrating AI into clinical decision-making.

3. Methodology

This section details the qualitative research design, data collection, and analytic approach employed to examine how clinicians dynamically calibrate artificial intelligence (AI) involvement in clinical decision-making.

3.1. Research design

This study adopts a qualitative, interpretive research design to examine how clinicians engage with AI in everyday clinical work (Klein & Myers, 1999; Walsham, 1995). Given the study's focus on moving beyond static notions of adoption and resistance, semi-structured interviews were used to explore clinicians' situated judgement, reasoning, and decisions regarding AI use across clinical situations. The interview design was informed by an existing, peer-reviewed framework of AI adoption and resistance in healthcare (Kaja et al., 2025), which served as a guiding conceptual lens rather than a set of propositions to be tested. Rather than treating AI adoption as a discrete outcome, the study examines how clinicians dynamically calibrate the extent, visibility, and authority of AI involvement in practice.

An interpretive approach is appropriate because it captures how meanings, evaluations, and uses of AI emerge through clinicians' situated professional practice and ongoing sensemaking (Orlikowski, 2000). Here, decision-making is understood not as an individual cognitive or rational-choice process, but as a professional practice enacted within clinical work and shaped by task demands, perceived risk, and accountability conditions.

3.2. Participants and data collection

Data were collected through semi-structured interviews with 29 clinicians across a range of healthcare specialisations, all of whom had direct experience using AI-supported tools in patient-care contexts. These included formally implemented systems (e.g. clinical decision support systems and diagnostic AI) as well as widely available AI tools used informally to support clinical reasoning, documentation, or information seeking.

Participants were recruited using purposive and snowball sampling to ensure variation in clinical roles, experience levels, and forms of AI engagement. The sample included physicians, nurses, and allied health professionals working in diagnostic, therapeutic, and procedural roles. While participants shared a common professional background, they were practising within different national healthcare systems, introducing variations in institutional and governance conditions without constituting a formal cross-country comparison.

The participant group included physicians from several specialities (e.g. family medicine, radiology, dermatology, paediatrics, endocrinology, emergency medicine, and ophthalmology), nurses working in emergency and operating room settings, medical laboratory specialists, radiologic technologists, radiographers, a respiratory therapist, an audiologist, and a medical physicist. Participants' professional experience ranged from 2 to 22 years, with the majority having between 5 and 10 years of clinical experience. The sample included 22 female and 7 male participants. This diversity of roles, experience levels, and clinical contexts helped capture varied perspectives on how AI is incorporated into clinical decision-making.

Semi-structured interviews were well suited to capturing clinicians' reflections on concrete situations in which AI was relied upon, cautiously verified, selectively consulted, concealed, or deliberately avoided. The interview guide was informed by the conceptual lens outlined earlier and was iteratively refined during data collection to probe emerging patterns of AI engagement across clinical situations. Interview questions focused on specific instances of AI use and non-use, how clinicians evaluated AI outputs, and how responsibility and accountability were managed when AI informed clinical decision-making.

Interviews were conducted between May and September 2025, lasted approximately 45–60 minutes, were audio-recorded with informed consent, and transcribed verbatim. Data collection and preliminary analysis proceeded iteratively and continued until no substantively new patterns of AI engagement were observed.

Table 1. Illustrative examples of open, axial, and selective coding showing the transformation from raw data to decision orientations.

Raw excerpt	Open coding (initial codes)	Axial coding (categories)	Selective coding (core category)
"I never depend on it blindly . . . the final judgement is always mine".	Verifying AI outputs	Human oversight	Cautious orientation
"Even if they don't want me to use it, I would still keep using it privately".	Using AI privately	Visibility management	Concealed orientation
"Simple tasks . . . I'm comfortable using it".	Using AI selectively by task	Task-based gating	Selective orientation
"The system diagnosed a patient . . . but that diagnosis was completely wrong".	Rejecting unreliable AI output	Diagnostic boundary-setting	Withdrawn orientation
"AI can efficiently handle routine and administrative tasks".	Using AI routinely for standard tasks	Workflow integration	Routine orientation

3.3. Data analysis

Data analysis followed an iterative, grounded-theory-inspired coding process that combined theory-informed guidance with inductive pattern identification (Charmaz, 2014; Strauss & Corbin, 1998). Transcripts were first analysed using open coding to identify recurring actions, evaluations, and judgements related to AI engagement in clinical work. Axial coding was then used to compare codes across cases and examine relationships between task characteristics, accountability considerations, and forms of AI involvement. Selective coding synthesised these patterns into higher-order categories representing distinct decision orientations. To enhance transparency in the analytical process, Table 1 provides illustrative examples of how interview excerpts were transformed through open, axial, and selective coding into the conceptual themes used in the analysis. Additional examples are provided in Appendix Table A1.

Specifically, open coding generated initial descriptive codes grounded in participants' statements, axial coding grouped these codes into higher-level categories reflecting patterns of AI engagement, and selective coding integrated these categories into overarching decision orientations, following established grounded theory procedures (Strauss & Corbin, 1998). Throughout the analysis, attention was paid to shifts in AI engagement across situations and over time, allowing decision orientations to be examined as dynamic patterns of action rather than sequential stages. Qualitative data analysis software (NVivo) was used to support systematic coding and organisation. Initial coding was conducted independently, and coding differences were discussed and reconciled through iterative comparison and interpretive consensus, ensuring consistency in code definitions and orientation classification. Decision orientations were conceptualised as situational configurations of AI engagement enacted at the level of specific clinical decisions, rather than as stable individual traits.

3.4. Rigor and ethical considerations

Analytical rigour was supported through constant comparison, attention to negative cases, reflexive memoing, and iterative engagement with the data (Lincoln & Guba, 1985). Ethical approval was obtained from the Social Research Ethics Committee, University College Cork (Log No: 2025–067). All participants provided informed consent prior to participation. Interview data were anonymised and securely stored in accordance with institutional and ethical guidelines.

4. Findings

The analysis identifies five decision orientations that clinicians enact when engaging with AI in clinical work: withdrawn, concealed, selective, cautious, and routine. These orientations describe recurring patterns through which clinicians regulate AI involvement in practice. Rather than representing fixed user types, the orientations capture different ways clinicians incorporate, limit, or exclude AI support in practice.

Across interviews, clinicians described regulating AI involvement along three interrelated dimensions: extent, visibility, and authority. While extent and visibility were most explicitly articulated, authority was reflected in how clinicians described the influence of AI on their final decisions.

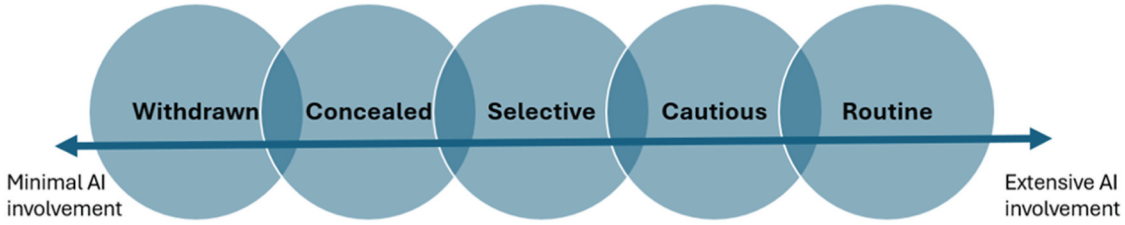


Figure 1. Dynamic decision space illustrating how clinicians recalibrate AI involvement across clinical situations.

Table 2. Configurations of AI involvement across decision orientations.

Decision Orientation	Extent of AI Involvement	Authority of AI Output	Visibility of AI Use	Typical Context
Withdrawn	None	None – clinical judgement fully independent of AI	Not applicable	High-risk diagnosis, legal accountability, sensitive patient data
Concealed	Present – AI is used but not openly acknowledged	Undisclosed – AI influence is not made explicit	Hidden	Legitimacy concerns, unclear institutional approval, reputational risk
Selective	Conditional – AI used depending on situation	Bounded – clinician retains full control	Visible	Task complexity, novelty, patient consent considerations
Cautious	Present – AI is used with consistent verification	Verified – influence only after validation	Visible	Complex or uncertain cases requiring verification
Routine	High-frequency, routine use	Minimal – limited to low-stakes or non-decision tasks	Typically visible	Administrative work, documentation, technical processes

Importantly, these patterns were not stable. Clinicians described shifting between them as task characteristics, perceived risk, accountability demands, and contextual constraints changed. AI engagement therefore emerges as an ongoing process through which clinicians recalibrate the role of AI across clinical situations.

Figure 1 presents the five decision orientations as a dynamic decision space. The double-headed arrow reflects reversible movement between orientations, while overlapping regions indicate flexible boundaries and situational transitions rather than fixed stages.

To further clarify these distinctions, Table 2 shows how the five orientations differ across the three dimensions of extent, authority, and visibility, making explicit how clinicians configure AI involvement under different conditions.

While Table 2 summarises the dominant characteristics of each orientation, the findings below show that clinicians move between them as situational conditions change.

4.1. Withdrawn orientation: AI explicitly excluded from decision-making

In the withdrawn orientation, clinicians deliberately exclude AI from decision-making when it is perceived as inappropriate, unsafe, or unjustifiable for the task at hand. This exclusion is primarily driven by concerns about reliability, accountability, and professional responsibility. For example, one clinician described how incorrect AI outputs reinforced their reluctance to rely on such systems: 'The system diagnosed a patient with a certain disease, but that diagnosis was completely wrong . . . this could lead to wrong referrals or treatment' (P16). This illustrates how experiences of unreliable outputs lead clinicians to actively reject AI involvement in diagnostic reasoning. In this orientation, AI involvement is absent: clinicians exclude AI entirely, with no reliance or decision influence, and visibility becomes irrelevant.

Diagnostic authority emerged as a firm boundary shaping this orientation. Clinicians consistently framed diagnosis as a non-delegable professional responsibility. As one participant explained, 'I don't think I would use AI to make the diagnosis itself because that's my responsibility as a specialist' (P6). Similarly, another clinician emphasized that 'the final decision remains my responsibility as a physician' (P23). These accounts show that withdrawal is not only driven by technological limitations but also by the need to preserve professional accountability and clinical authority.

Withdrawal was also shaped by governance and legal concerns, particularly in situations where responsibility or authorisation was unclear. For example, one clinician noted, 'I avoid uploading patient images because we're worried about confidentiality' (P21). This reflects how institutional ambiguity and lack of clear

guidelines can reinforce non-use, even when AI may be technically available. In such cases, clinicians preferred to rely on established clinical procedures rather than introducing AI into legally or ethically sensitive contexts.

Importantly, withdrawal was often situational rather than a general rejection of AI. Many clinicians reported using AI in other parts of their work but intentionally excluding it from high-risk, diagnostic, or time-critical decisions. This suggests that withdrawal operates as a protective boundary around core clinical judgement, enacted when perceived risks and accountability demands outweigh the potential benefits of AI.

4.2. Concealed orientation: private use without visible reliance

In the concealed orientation, clinicians continue to use AI while intentionally withholding disclosure of that use. Here, the key issue is not whether AI is useful, but whether its visible use is perceived as professionally acceptable. Clinicians described deliberately separating private use from public disclosure to manage professional identity, institutional expectations, or patient trust. For example, one clinician explained: 'Even if they don't want me to use it, I would still keep using it privately' (P7). This suggests that concealment is not driven by rejection of AI, but by concerns about how its use is perceived by others. In this orientation, AI is used but kept in the background, with its influence remaining implicit rather than openly acknowledged in decision-making contexts.

Concealment occurred both in interactions with colleagues and in patient-facing situations, particularly when clinicians anticipated scepticism or feared undermining trust. For instance, one participant described adjusting how openly they disclosed AI use depending on the audience: 'For certain things, it's okay to say I used AI ... but for other things, when I'm talking with people who are more senior, I try to be more conservative and not mention AI too much' (P6). These accounts show that visibility of AI use is actively managed in relation to professional hierarchies and expectations.

Shared professional norms further reinforced this pattern, as one clinician noted, 'Everyone uses it, but no one admits it openly, especially with older generations' (P1). This reflects a collective understanding in which AI use is normalised in practice but selectively concealed in professional discourse.

Organisational non-endorsement further reinforced this orientation by creating uncertainty about legitimacy and accountability. In the absence of clear governance or formal protections, clinicians perceived openly acknowledging AI use as professionally risky. For example, one participant explained: 'I feel that without laws, it's like using AI "under the table". If I rely on it, I won't be protected' (P28). This shows how institutional ambiguity shapes not only whether AI is used, but whether its use can be safely disclosed.

Concealed use therefore centres on managing the visibility of AI involvement rather than its actual use. Rather than reflecting rejection of AI, concealment reflects a strategic response to professional norms, organisational ambiguity, and perceived reputational risks. This indicates a disconnect between actual AI engagement and visible adoption, where clinicians continue to rely on AI while selectively limiting how that reliance is presented in professional contexts.

4.3. Selective orientation: conditional and situational AI use

The selective orientation reflects conditional engagement, in which clinicians actively decide whether and when AI should be involved in a given situation. Rather than rejecting or routinely relying on AI, clinicians selectively activate it depending on situational demands. In this orientation, AI involvement is characterised by conditional extent, visible use, and bounded authority, as clinicians selectively engage AI while retaining full control over its evaluation and final judgement.

As one clinician explained, 'AI is present as a supportive tool, but its use is still limited ... I don't rely on it in all cases' (P14). This indicates that AI is treated as an optional resource rather than a default component of decision-making. Clinicians described actively gating AI use based on the nature of the task and the level of clinical risk involved.

Selectivity was primarily governed by task severity, complexity, and uncertainty. For example, one clinician noted: 'Simple tasks ... I'm comfortable using it. Critical cases ... I rely on my own judgement' (P12). Similarly, another participant explained: 'For calculations and reporting, it's okay ...

For diagnosis, it isn't' (P7). These distinctions show how clinicians establish boundaries around where AI can and cannot be appropriately applied, particularly separating low-risk or supportive tasks from core diagnostic decisions.

Clinicians used AI as a bounded cognitive resource, often to generate options or support reasoning, while retaining full control over evaluation and final judgement. This pattern was particularly evident in situations involving unfamiliar or complex cases. As one clinician explained, 'For practical lab work, I never rely on AI . . . But when I face something new . . . that's when I go to AI to guide me' (P26). This suggests that AI is mobilised as a situational support tool when existing expertise is insufficient, rather than being used consistently across tasks.

Ethical considerations, including patient consent, further shaped selective engagement. For example, one participant explained: 'I would never use AI on a patient who doesn't want it . . . I'd just avoid it in cases where the patient is uncomfortable' (P10). This highlights how ethical constraints act as an additional gating mechanism, influencing whether AI is introduced into the decision process at all.

Selective use therefore centres on deciding whether AI should be involved in a given decision, rather than how its outputs are evaluated once involved. This indicates that clinicians continuously calibrated AI involvement based on task characteristics, clinical responsibility, and contextual constraints, treating AI as a conditional resource that is activated, limited, or excluded depending on situational demands.

4.4. Cautious orientation: AI as a verified second opinion

In the cautious orientation, clinicians engage with AI while maintaining full responsibility and authority over decisions. Unlike selective orientation, which governs whether AI is involved, cautious orientation governs how AI outputs are evaluated once AI is already part of the decision process. AI outputs are treated as provisional inputs that require verification before influencing judgement. As one clinician explained: 'I never depend on it blindly . . . the final judgement is always mine' (P8). This indicates that clinicians position AI as a secondary input that must be validated rather than uncritically accepted. In this orientation, AI involvement is characterised by present extent, visible use, and verified authority, as clinicians actively engage AI while requiring its outputs to be validated before influencing clinical judgement.

Clinicians consistently emphasised that AI-generated suggestions require verification against clinical evidence, patient context, and professional judgement before being considered actionable. For example, one participant noted: 'I wouldn't take it as absolute truth. I'd cross-check it with reliable sources or consult a specialist' (P25). This shows that verification practices are embedded within clinical reasoning rather than treated as optional steps.

Caution was reinforced by concerns about reliability and explainability, particularly in high-stakes situations. Clinicians described actively validating AI outputs through independent reasoning and additional information sources before acting on them. For example, one clinician noted: 'I ask ChatGPT for a starting point or quick insight, and then I check it against the medical references' (P24). This suggests that AI outputs function as entry points for further evaluation rather than as decision endpoints. Similarly, another participant noted: 'It might suggest a diagnosis I hadn't considered . . . then I go and research that diagnosis myself' (P4). These accounts show how AI is used to expand diagnostic possibilities while preserving clinician-led validation.

When clinicians perceived AI outputs as opaque, inconsistent, or difficult to interpret, reliance remained limited and verification intensified. Lack of transparency or uncertainty about how outputs were generated reduced clinicians' willingness to rely on AI without additional scrutiny. As one clinician explained: 'It affects my confidence' (P1). This shows that trust in AI depends on how understandable its outputs are, which influences how carefully clinicians check them.

Cautious engagement therefore centres on sustained human oversight, where AI serves as a -verified second opinion rather than a decision authority. This reflects a form of controlled reliance in which AI contributes to decision-making but remains subordinate to clinician judgement. As one participant summarised, 'I mainly use it as a double-check, not a substitute' (P23).

4.5. Routine orientation: integrated and low-verification use

In the routine orientation, AI is seamlessly integrated into everyday workflows, particularly for low-risk, repetitive, or administrative tasks. Use becomes habitual, verification is minimal, and AI support is often taken for granted as part of normal clinical practice. As one clinician explained, 'AI can efficiently handle the routine and administrative tasks … saving significant time and effort' (P14). This indicates that AI is primarily used as an efficiency tool embedded within routine workflows rather than as an active decision aid. Clinicians frequently described AI as integrated into activities such as documentation, information organisation, and technical workflow support, where the stakes are relatively low and outputs can be easily reviewed if needed. In this orientation, AI involvement is characterised by high-frequency extent, typically visible use, and minimal authority, as AI is routinely embedded in workflows and used with limited need for active verification or influence on core clinical judgement.

AI was framed as an embedded assistant rather than a decision authority, supporting automation and delegation of standardised processes. For example, one clinician noted that 'all of us rely on it; nobody really does manual calculations anymore' (P7). This shows how AI-supported tools have become normalized and expected within everyday technical tasks. Similarly, clinicians described using AI to assist with documentation and reporting, allowing them to redirect attention towards more complex aspects of patient care.

Routine use was justified by efficiency gains and indirect benefits for patient care. For instance, one participant explained: 'It takes less time so I can focus more on patient care' (P11). This highlights how routine AI use is valued for saving time and supporting clinical work rather than directly influencing decisions. In some cases, AI functionality was already embedded within clinical technologies, performing tasks such as image adjustments or preliminary analysis automatically as part of standard workflows (P8).

Despite this normalisation, escalation pathways remained in place for abnormal or high-risk cases. Clinicians emphasised that routine reliance applied primarily to standardised, low-risk tasks, while more complex or uncertain situations triggered additional verification or shifts towards more cautious orientations. This shows that routine use does not remove oversight but coexists with mechanisms for adjusting AI involvement when needed.

Routine use therefore reflects the normalisation of AI as background infrastructure within stable workflows, where it is no longer actively evaluated but implicitly relied upon. Over time, repeated exposure and consistent performance reinforce familiarity and trust, allowing AI to become an integrated but largely invisible component of everyday clinical practice.

4.6. Transition dynamics: recalibrating AI involvement

Clinicians did not remain within a single decision orientation but recalibrated AI involvement as task demands, perceived risks, accountability conditions, and workflow constraints changed. These shifts were enacted through adjustments in the extent, visibility, and authority of AI involvement. Rather than following a fixed progression, clinicians dynamically shifted between orientations depending on how they evaluated the appropriateness of AI involvement in a given situation. For example, one clinician described adjusting AI use based on task criticality: 'For simple tasks … I'm comfortable using it. Critical cases … I rely on my own judgement' (P12). This shows how clinicians move between routine, cautious, and withdrawn orientations based on perceived risk and decision impact.

Clinicians also described delegating routine or administrative tasks to AI with minimal scrutiny, while reserving diagnostic or high-stakes decisions for more cautious verification or complete exclusion of AI. This indicates that AI involvement is continuously adjusted in response to changing clinical conditions rather than applied consistently across tasks.

Transitions were triggered by evaluative cues such as conflicts between AI outputs and clinical judgement, concerns about reliability or explainability, and workflow misalignment. For instance, when AI outputs appeared inconsistent or difficult to interpret, clinicians shifted from routine or selective use towards more cautious verification practices. Conversely, repeated positive experiences and familiarity with AI tools supported movement towards routine integration, particularly in stable and standardised workflows. These patterns show that shifts in AI use are driven by ongoing evaluation rather than fixed preferences.

Recalibration also occurred along a visibility dimension, with clinicians sometimes continuing to use AI while modifying how openly that use was disclosed. For example, clinicians described maintaining AI use while shifting from visible to concealed engagement in order to manage professional legitimacy or accountability concerns. This suggests that transitions involve not only how much AI is used, but also how its use is presented within professional contexts.

Taken together, these findings demonstrate that AI engagement is not a stable adoption outcome, but a dynamic, situated practice in which clinicians continuously recalibrate how AI is used, evaluated, and presented in response to evolving clinical conditions. The five orientations therefore represent a flexible decision space through which clinicians actively regulate when AI should be excluded, selectively engaged, cautiously verified, routinely integrated, or strategically concealed.

5. Discussion

This study shows that clinicians' engagement with AI cannot be adequately explained through stable categories of adoption or resistance. Instead, clinicians enact five recurring decision orientations (withdrawn, concealed, selective, cautious, and routine) through which they dynamically configure the extent, visibility, and authority of AI involvement. This suggests that AI engagement is not a fixed user disposition, but a situated process in which professionals continuously regulate the role of AI within individual decision contexts. Together, these findings reconceptualise AI engagement in clinical work as an ongoing process of decision calibration, through which clinicians maintain professional judgement and responsibility.

Importantly, these orientations are structured through three interrelated dimensions: extent, visibility, and authority, which together define how AI involvement is configured within decision-making processes. Rather than applying AI in a uniform or stable manner, clinicians actively adjust these dimensions in response to situational conditions, indicating that AI use operates as a dynamic configuration rather than a stable behavioural outcome.

The findings further show how contextual conditions shape this calibration process in practice. Task demands, perceived risk, and accountability conditions influence whether and how AI is involved in a decision. When tasks involve high uncertainty or significant patient risk, clinicians reduce the extent of AI involvement and limit the authority granted to AI recommendations, often shifting towards cautious or withdrawn orientations. In contrast, routine or administrative tasks enable greater AI extent with lower verification requirements, resulting in routine orientations. Situations involving professional scrutiny, unclear governance, or reputational concerns influence the visibility of AI use, leading clinicians to conceal AI involvement even when it informs their reasoning. These patterns suggest that clinicians translate situational evaluations into specific configurations of AI involvement, rather than making one-time adoption decisions.

Taken together, the five orientations represent distinct but fluid configurations of extent, visibility, and authority through which clinicians regulate AI involvement in practice. Rather than fixed categories, they illustrate how professionals actively organise AI engagement in response to varying demands for efficiency, verification, accountability, and legitimacy. By conceptualising AI engagement as the dynamic configuration of these dimensions, this study shifts the focus from whether AI is adopted to how its role is continuously regulated within professional decision-making.

5.1. Theoretical implications

This study contributes to information systems research by developing a process-oriented account of human – AI engagement centred on decision calibration, which we conceptualise as the mechanism through which professionals regulate the extent, visibility, and authority of AI across decision contexts. Unlike prior models that explain whether technologies are adopted, this perspective explains how AI involvement is dynamically configured within individual decisions, and is consistent with emerging calls for human-centric IS research on evolving healthcare provider roles (Bardhan et al., 2025).

By foregrounding how professionals regulate these dimensions in response to situational conditions, this study introduces a process-oriented conceptualisation of human–AI engagement that is particularly relevant in judgement-intensive settings where accountability cannot be delegated. Although derived from

healthcare, this mechanism likely applies to other professional domains such as law, finance, and aviation, where AI informs but does not replace human decision authority.

First, the findings refine existing adoption and post-adoption perspectives by showing that overall usage patterns do not necessarily reflect how professionals engage with AI at the decision level. Frameworks such as TAM and UTAUT conceptualise adoption as an outcome reflecting users' overall orientation towards a technology (Davis, 1989; Venkatesh et al., 2003), while post-adoption models emphasise trajectories such as continued use or discontinuance (Bhattacherjee, 2001). These approaches are useful for explaining overall acceptance patterns, but they provide limited insight into how the same professional may variably rely on, scrutinise, conceal, or exclude AI across different decision situations (Jasperson et al., 2005). Our findings shift attention from global adoption attitudes to the situated configuration of AI involvement within specific decisions.

Second, this study introduces decision orientations as a process-oriented concept explaining how clinicians regulate AI involvement in practice. Decision orientations represent recurring socio-cognitive patterns that emerge as clinicians calibrate AI involvement across the dimensions of extent, visibility, and authority in response to accountability demands, perceived risk, and task conditions. Instead of classifying users into fixed categories, decision orientations describe recurring ways clinicians organise AI involvement across situations. This moves beyond identifying determinants of adoption to explaining how professionals actively configure the role of AI within their work. These insights build on prior qualitative studies highlighting trust, explainability, and professional identity in healthcare AI (Amann et al., 2023; Fazakarley et al., 2023; Moldt et al., 2025). Adoption and resistance therefore emerge as situational outcomes of ongoing decision calibration, rather than stable user positions.

Third, the findings surface forms of AI engagement that are often obscured or misclassified in existing adoption and use theories, particularly concealed use and principled withdrawal. Concealed use shows that AI may substantially shape clinical judgement even when its involvement is deliberately kept invisible, challenging the assumption that observable or reported use reliably indicates adoption. Withdrawal, in contrast, emerges not as inertia or resistance, but as an active boundary-setting practice through which clinicians protect professional responsibility in the presence of unresolved concerns about reliability, authorisation, or legal accountability. These forms of engagement extend existing theories by showing that non-use and hidden use can represent purposeful and contextually rational practices rather than deviations from adoption (Baumer et al., 2015; Jasperson et al., 2005).

Fourth, the findings highlight the transition dynamics through which clinicians move between orientations as decision conditions change. Rather than remaining within a single engagement pattern, clinicians shift between routine use, cautious verification, selective activation, concealment, or withdrawal depending on how they evaluate risk, responsibility, and professional legitimacy in a given situation. These transitions indicate that AI engagement is shaped by decision-level recalibration rather than by stable user attitudes or linear adoption trajectories. This extends process-oriented views of technology use by demonstrating how professionals continuously reconfigure AI involvement across tasks, interactions, and organisational contexts.

Taken together, these contributions suggest that theories of AI adoption should complement outcome-based explanations with process-oriented accounts of how professionals regulate AI involvement within specific decision contexts. Together, decision calibration and decision orientations explain how AI is not simply adopted, but dynamically configured and enacted within professional decision-making.

5.2. Practical implications

The findings suggest that effective AI integration should not presume uniform or continuous use. Instead, implementation strategies should support variations in engagement and safe movement between orientations.

5.2.1. Design implications

AI systems should support different degrees of involvement and verification through adjustable review features, optional checks, and flexible activation. For cautious engagement, clinicians require explainability

and efficient verification mechanisms. For selective engagement, flexible access allows AI to be activated when appropriate. Systems should also make AI involvement visible and reviewable when needed, supporting transparency while preserving clinician autonomy. The presence of concealed and withdrawn orientations further highlights the importance of supporting professional autonomy and legitimacy.

5.2.2. Implementation implications

Concealment and withdrawal should be interpreted as diagnostic signals rather than non-compliance. Concealment may indicate uncertainty about approval or accountability, while withdrawal may reflect misalignment between AI capabilities and clinical responsibility. Implementation efforts should prioritise clarifying responsibility boundaries, improving workflow fit, and legitimising context-dependent use rather than enforcing uniform uptake.

5.2.3. Training implications

Training should be ongoing and adaptive rather than a one-time intervention. Because clinicians recalibrate engagement across orientations, training should support selective and cautious uses, recognise appropriate disengagement, and enable safe re-engagement as conditions evolve. Reduced use should not automatically be interpreted as a skills deficit.

5.3. Organisational and governance implications

The findings call for orientation-sensitive governance in which variability in AI use is anticipated and governed rather than suppressed. Governance approaches that equate visible use with adoption risk misunderstanding how AI shapes clinical judgement. This highlights a misalignment between observable use and actual decision influence, which existing governance approaches often fail to capture.

Concealed use reveals a governance blind spot. When clinicians rely on AI privately due to uncertainty about approval or accountability, organisations lose visibility into how AI influences decision-making. Addressing this requires clear definitions of acceptable uses, responsibility boundaries, and disclosure norms.

Withdrawn orientations should similarly not be interpreted as opposition to innovation. Withdrawal often reflects principled boundary-setting under legal ambiguity or unclear accountability. Governance approaches that penalise withdrawal risk encouraging superficial compliance or concealment. Orientation-sensitive governance instead recognises variability in engagement as a feature of responsible clinical practice, enabling sustainable and accountable AI integration.

6. Conclusion

Taken together, the findings show that AI engagement in healthcare is best understood as an ongoing process of decision calibration shaped by task demands, perceived risk, accountability pressures, and contextual constraints. Rather than occupying stable positions as adopters or resistors, clinicians dynamically adjust the extent, visibility, and authority of AI involvement as clinical situations evolve. By foregrounding decision orientations and their transitions, this study moves beyond static adoption and resistance models and recentres professional judgement as the organising principle of AI-supported clinical work. In doing so, it makes visible forms of engagements such as selective use, concealed reliance, and principled withdrawal that are often obscured or misclassified in dominant theories. Conceptualising AI engagement in this way provides a more accurate account of how clinicians manage responsibility, risk, and legitimacy in AI-supported decision-making, and offers a process-oriented contribution to information systems and healthcare AI research.

6.1. Limitations and future research

This study is based on qualitative interview data and captures clinicians' reported decision-making rather than direct observation of AI use. Future research could complement interviews with observational, ethnographic, or system-level data to examine how decision orientations are enacted in practice. The study

focused on clinicians with experience using AI-supported tools and did not aim to conduct formal cross-context comparisons. Future work could examine how decision orientations vary across healthcare systems, regulatory environments, and levels of AI maturity, and explore their implications for patient trust, safety, and sustainable AI integration. The concept of decision orientations may also be extended to other high-stakes professional domains characterised by judgement and accountability.

Author contributions

CRediT: **Rania Kaja:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Karen Neville:** Conceptualization, Supervision, Writing – review & editing; **Stephen Treacy:** Conceptualization, Supervision, Writing – review & editing; **Simon Woodworth:** Conceptualization, Supervision, Writing – review & editing.

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The data are not publicly available due to privacy restrictions but are available from the corresponding author upon reasonable request.

Use of generative AI

During manuscript preparation, ChatGPT was used for language editing. The authors reviewed the output and took full responsibility for the content.

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Appendix

Table A1. Analytical traceability showing coding structure from raw data to decision orientations.

Raw excerpt	Open coding (initial codes)	Axial coding (categories)	Selective coding (core category)
"I don't think I would use AI to make the diagnosis itself because that's my responsibility as a specialist". (P6)	Avoiding AI in diagnosis	Diagnostic boundary-setting	Withdrawn orientation
"Everyone uses it, but no one admits it openly, especially with older generations" (P1).	Using AI privately	Visibility management	Concealed orientation
"For calculations and reporting, it's okay . . . For diagnosis, it isn't". (P7)	Using AI selectively by task	Task- based gating	Selective orientation
"I wouldn't take it as absolute truth. I'd cross-check it with reliable sources". (P25)	Verifying AI outputs	Human oversight	Cautious orientation
"All of us rely on it; nobody really does manual calculations anymore" (P7).	Using AI routinely for standard tasks	Workflow integration	Routine orientation