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AI IN PRACTICE

A techno-anthropological approach for integrating AI into healthcare

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Abstract

Artificial intelligence is increasingly deployed in healthcare. Radiology is one of the most active areas of clinical AI development. Despite substantial investments, many AI systems struggle to gain traction in clinical practice. The issues are rarely purely technical; they concern how AI tools fit into existing workflows, how they interact with professional responsibilities, and how they sit within institutional arrangements. It also remains unclear how core values in AI research such as explainability, value alignment, accountability, and trust are negotiated in clinical work. Established Health Technology Assessment (HTA) models define assessment domains but offer limited guidance on implementation: how technologies are staged within workflows, how responsibilities are redistributed, and how local conditions redefine value for different stakeholders. This paper presents the *AI in PRACTICE* framework, a five-phase methodology grounded in Techno-Anthropology and its relational ontology, for examining the situated work through which AI becomes part of clinical practice. Explainability, value alignment, trust, and distributed responsibility are understood as produced through socio-technical practices. The framework complements existing HTA models through iterative engagement and stakeholder participation. Insights are illustrated through three radiology-facing AI projects showing how assessment criteria are enacted, resisted, and revised in context, and how the framework generates practice-based artefacts.

Plain Language Summary¹

- This study is relevant for hospital managers, clinicians, IT and governance staff, and AI developers involved in bringing AI tools into clinical workflows. It shows why many AI systems that perform well in testing still struggle to gain traction in real hospital settings.
- The article argues that AI integration problems are rarely purely technical. Existing assessment models define what to evaluate (safety, effectiveness, ethics, economy) but offer little guidance on how AI is staged into workflows, how responsibility shifts, and how local conditions redefine value for different stakeholders.
- Drawing on Techno-Anthropology, the article presents "AI in PRACTICE," a five-phase framework (Lead-in, Workflow Contextualisation, Alignment, Co-creative Implementation, and Assessment and Empowerment) for examining the situated work through which AI becomes part of clinical practice.
- Based on ethnographic fieldwork across three radiology AI projects in Denmark, the study shows how explainability, trust, and accountability are not fixed properties of a system but are negotiated case by case, shaped by workflow timing, interface visibility, and professional roles.
- The findings offer hospitals and developers a practical, staged approach for identifying potential barriers to AI integration, complementing existing assessment models by making visible the socio-technical work needed to decide whether and how AI tools should be continued, modified, scaled, or stopped.

¹ AI-generated; author checked and approved.

1 INTRODUCTION

Artificial intelligence is increasingly positioned in national and international healthcare strategies as a priority technology for improving safety, efficiency, and decision quality in clinical work (Deloitte Centre for Health Solutions, 2020; European Commission: Directorate-General for Health and Food Safety, 2019; World Health Organization, 2021). Similarly, digital health, including AI-driven decision support, is now a standing item on policy agendas in Denmark and across Europe, with sustained public and private investment (Abernethy et al., 2022).

AI in radiology is similarly gaining attention for several reasons. The demand for radiological examinations has risen sharply over the past two decades, driven by aging populations, expanded screening programmes, and the growth of cross-sectional imaging as a standard diagnostic tool (McDonald et al., 2015; Brink & Hricak, 2022). Radiologist workload has risen in step, and dramatic increases in on-call workload have been documented over the past fifteen years (Bruls & Kwee, 2020). Supply of radiologists has not kept pace with demand. Concerns about workload sustainability and clinician burnout are a recurring theme in the radiology literature (Kwee & Kwee, 2021). AI is widely positioned as one response to this pressure, with the argument that decision-support tools can absorb parts of the analytic workload, prioritise acute cases, and support consistency in interpretation (Brink & Hricak, 2022; Kwee & Kwee, 2021).

Image interpretation is the task where machine learning has matured earliest, and decision-support tools for radiological workflows are now one of the most active areas of clinical AI development (Choy et al., 2018; Letourneau-Guillon et al., 2020; Sheng et al., 2022). Commercial products in medical imaging AI have expanded rapidly over the past decade, with more than one hundred AI products already available for clinical deployment across imaging modalities (van Leeuwen et al., 2021). These systems are regulated as medical devices, carry CE marking in Europe or FDA clearance in the United States, and hospitals now encounter them as procurement options with formal regulatory standing (van Leeuwen et al., 2021). The question facing hospitals is no longer whether clinical AI exists. It is how to integrate it.

Despite promises, AI systems struggle to gain meaningful traction in clinical practice, and a growing focus in the literature documents the gap between technical performance and clinical uptake (Gerdes, 2024; Ocloo et al., 2020; Saghafian et al., 2021). Systems that demonstrate high accuracy in retrospective studies do not always translate into usable clinical tools. Pilots stall and workflows resist the insertion of new decision-support steps. Clinicians discount outputs they cannot act on in time. Still, the issues are not primarily technical. They concern how AI tools fit, or fail to fit, into existing workflows, how they interact with professional responsibilities and institutional arrangements, and how values such as explainability, value alignment, accountability, and trust are negotiated when a system becomes part of clinical work (Nielsen et al., 2026).

Integration problems of this kind are not specific to AI. The history of health informatics contains many examples of technologies that performed well in controlled settings and then failed in clinical use because the organisational, infrastructural, and workflow conditions of that use were not adequately understood (Botin et al., 2015a, 2015b). AI adds particular difficulties to these older patterns. AI systems are probabilistic, carry interpretive uncertainty that has to sit somewhere in the clinical division of labour, and update through retraining cycles that do not match hospital procurement or governance timelines. Regulatory categories for AI are still being stabilised. The classification of a deployment as medical device testing or as workflow change shapes which institutional review pathway applies, what evidence is required, and who carries responsibility when something goes wrong. These are not edge cases. They are features of the terrain in which AI adoption now takes place.

The prevailing response to challenges to the integration of digital technologies in health care has been to develop assessment frameworks. In the Danish and broader European contexts, the most prominent are Health Technology Assessment (HTA) models and their Danish variants: Medical Technology Assessment (MTV) (Center for Evaluering og Medicinsk Teknologivurdering [CEMTV], 2005) and the Model for Assessment of Telemedicine (MAST) (Kidholm et al., 2017). The same response pattern has now extended to AI integration, where MAST has evolved into the Model for Assessment of Artificial Intelligence (MAS-AI). This assessment model builds on the principles of MTV and MAST, but tailors them to AI in medical imaging (Fasterholdt et al., 2022). What these frameworks provide are structured domains and criteria for assessment, such as effectiveness, safety, organisational impact, ethics, and economy, and they operate practical repertoires that format what kinds of evidence and justification are considered legitimate. These models have known limitations, including resource intensity, slow adaptation to rapidly evolving technologies, and limited guidance on how technologies become workable in practice. The core point is that these frameworks share a common orientation: they are designed to provide structured, comprehensive assessment of healthcare technologies. Namely, they are designed to define what should be assessed and reported when a technology is approved for implementation. They produce (sometimes classified) reports intended to inform institutional decision-making about whether and how to adopt a given technology, but offer limited guidance on the work preceding the implementation, addressing how technology is staged in the workflow, how responsibility is redistributed, and how local constraints reshape what counts as valuable. The three HTA frameworks share a common analytical limitation that becomes particularly visible with AI, where the object of assessment is often unstable across sites, updates frequently, and depends on local conditions of infrastructure, timing, and role boundaries for its usefulness. Thus, they are less equipped to address the work that makes the assessment object coherent, the negotiation of stakeholders' values (hospital management, clinicians, IT infrastructure, technology providers), the staging of workflow changes, the redistribution of responsibilities, and the institutional arrangements that determine whether and how an AI technology enters clinical practice.

In response, this paper presents the *AI in PRACTICE* framework, a five-phase methodology for examining and supporting the situated work through which AI becomes, or fails to become, part of clinical practice. The central argument of the paper is that the situated conditions through which AI becomes workable belong at the centre of integration work and cannot be assessed after implementation alone. These conditions include infrastructural timing, interface visibility, professional role boundaries, governance classifications, and the organisation of interpretive burden under time pressure. The framework is grounded in the Techno-Anthropology research tradition developed at Aalborg University, and its five phases (Preliminary Lead-in, Workflow Contextualisation, Alignment as Staging and Negotiation, Co-creative Implementation, and Assessment and Empowerment) address questions of staging and implementation that existing HTA models neglect. The analytical advantages of the framework are illustrated through ethnographic fieldwork carried out across three radiology-facing AI projects conducted between 2019 and 2026, where these questions of staging and implementation were repeatedly decisive for whether AI adoption moved forward or stalled. This shows the importance of preliminary socio-technical assessment beyond purely technical considerations.

Overall, while the *AI in PRACTICE* framework shares with existing HTA models the commitment to systematic, evidence-based engagement with health technologies, it differs in what is covered and how work is structured. Table 1 below unfolds these differences, identifies the limitations, and sets out the broader critique that the *AI in PRACTICE* framework takes up. While the work presented here is situated in radiology, we expect that this extended socio-technical approach and the framework devised here will also be relevant to other AI implementation processes in other areas of healthcare.

Table 1: Comparison Matrix of the three HTA models with the AI in PRACTICE framework.

Model	Shared ground with AI in PRACTICE	Distinctive features	Main practical limitations for AI integration	How AI in PRACTICE differs analytically (see section 5)
MTV (<i>Medicinsk Teknologivurdering</i>)	Comprehensive assessment of health technologies across four domains: technology, patient, organisation, and economy (Sundhedsstyrelsen, 2005).	Broad HTA framework applicable across many kinds of medical technologies; strong emphasis on effectiveness, patient outcomes, organisation, and costs.	Can be resource-intensive and difficult to operationalise in rapidly changing settings (Draborg, 2006); may be less suited to capture emergent workflow frictions, shifting responsibilities, and local negotiations around new technologies. It neglects organisational issues and non-technological or administrative contexts (Clemensen, 2000) and barely addresses ethical issues (Jensen et al. 2025).	AI in PRACTICE does not replace this broad evaluative perspective; rather, it complements it by documenting how value, evidence, and accountability are negotiated in concrete clinical settings before and during implementation. It foregrounds socio-technical relations, workflow consequences, and the local work required to make AI actionable in practice.
MAST (<i>Model for Assessment of Telemedicine</i>)	Structured assessment of clinical, organisational, economic, ethical, legal, and socio-cultural dimensions of digital health interventions (Kidholm et al., 2017).	Designed specifically for telemedicine; organised around study preparation, domain-based assessment, and transferability of results.	Extensive evidence requirements and broad domain coverage can make it demanding to apply in fast-moving implementation settings; and it does not in itself specify how local actors negotiate the practical fit of a technology in ongoing work (Ekeland et al., 2010; Kidholm et al., 2017; Vis et al., 2020).	AI in PRACTICE differs by focusing on AI and not on telemedicine. It also differs as to addressing the situated processes through which a technology becomes workable, interpretable, and legitimate in practice. It is especially concerned with how workflow fit, visibility, responsibility, and explanatory needs are staged and negotiated locally.
MAS-AI (<i>Model for Assessing the Value of Artificial Intelligence in Medical Imaging</i>)	AI-specific assessment organised in two steps across nine domains (health problem and current technology; technology; ethical aspects; legal aspects; safety; clinical aspects; economic aspects; organisational aspects; patient aspects), supplemented by five process factors covering model maturity, multidisciplinary, and reassessment (Fasterholdt et al., 2022).	Tailored to medical imaging AI; builds on HTA traditions while attending to AI-relevant criteria such as robustness, transparency, and ethical considerations.	Standardised assessment criteria may be too general and difficult to apply across heterogeneous and rapidly evolving AI applications, and they may not fully capture how outputs are interpreted, contested, or embedded in real clinical workflows (Gerdes 2024).	AI in PRACTICE complements MAS-AI by shifting attention from what should be assessed to how evaluation criteria themselves become meaningful in context. It highlights how explainability, usefulness, and trust are not only properties of the system, but practical accomplishments shaped by timing, interfaces, professional roles, and institutional constraints.

The remainder of the article proceeds as follows. Section 2 sets out the techno-anthropological grounding of the *AI in PRACTICE* framework and clarifies its ontology, as well as the conceptual and practical implications emerging from this grounding, including how it reshapes fundamental concepts in AI research such as explainability and trust. Section 3 describes the empirical basis of the framework across three radiology-facing AI projects. Section 4 presents the five phases in detail and illustrates each phase with examples from the fieldwork. Section 5 discusses the analytical insights of the *AI in PRACTICE* framework, including how it relates to existing HTA models. Section 6 concludes that the *AI in PRACTICE* framework complements these existing models by attending to the situated conditions through which explainability, value alignment, trust and accountability are produced and contested in clinical practice.

2 A TECHNO-ANTHROPOLOGICAL APPROACH TO HEALTH TECHNOLOGY ASSESSMENT

The theoretical grounding of the *AI in PRACTICE* framework (which embodies its socio-technical rationale) is Techno-Anthropology (TAN), an interdisciplinary research tradition developed at Aalborg University since the early 2010s (Børsen & Botin, 2013; Jensen, 2013; Wellner et al., 2015). Techno-Anthropology bridges STEM and SSH, drawing on technical domains such as AI, digitalisation, environmental and energy engineering, alongside anthropology, Science and Technology Studies (STS), Philosophy of Technology (PoT), and Participatory Design (PD). The tradition is reflected in work across these domains, including AI integration in radiology (Nielsen et al., 2026), environmental and sustainability research (Børsen et al., 2025; Valderrama Pineda et al., 2024; Teli et al., 2025), energy engineering (de Godoy et al., 2022), anthropology of expertise (Bruun & Krause-Jensen, 2022), STS-informed analysis of expert practices and infrastructures (Abildgaard et al., 2017; Birkbak et al., 2015; Jensen, 2020), philosophy of technology (Børsen, 2020; Botin et al., 2020), and participatory design (Christensen, 2013; Kanstrup et al., 2014; Teli et al., 2020). Within health informatics specifically, work in this tradition has focused on understanding why technologies that perform well in controlled settings often fail in clinical use, and on identifying the organisational, infrastructural, and professional conditions that shape successful integration (Botin et al., 2015a, 2015b; Amanatidis & Børsen, 2024; Knudsen, 2024). The framework presented in this article draws on this strand of TAN and takes those conditions as its primary object of analysis.

Lars Botin, Tom Børsen and others have applied the techno-anthropological lens to technology assessment (Børsen, 2021; Botin & Børsen, 2024). In their chapter in the Handbook of Technology Assessment, Botin and Børsen (2024) identify Techno-Anthropological Technology Assessment (T-ATA) as characterised by its focus on socio-technical configurations rather than isolated artefacts, its eclectic and bricolage-based methodology, and its commitment to embedding technologies within real social, cultural, and ethical contexts. It begins from the premise that technologies are always entangled with users, experts, institutions, and practices, and therefore requires methods that translate between these worlds. As the chapter states, T-ATA "sets out to assess socio-technical configurations, and not just technical artefacts" (p. 291) and is deliberately eclectic, designing its methodology case by case rather than following a single model. It addresses both existing and emerging technologies, including future visions, and aims to shape technological development responsibly by integrating ethical values, stakeholder participation, and contextual sensitivity into every stage of assessment.

A common denominator runs through the TA approach: the underlying relational ontology. Here, technologies are not treated as objects with fixed properties that exist independently of the contexts in which they are used. They are treated as enacted through relations with people, infrastructures, institutional arrangements, and material artefacts. The properties that matter, including value-ladenness, accuracy, usability, and explainability, are produced through these

relations and can change as these relations change. The relational ontology implies that the meaning and usefulness of an AI system cannot be read off its technical specifications. The question "does this AI work?" has to be asked in relation to a specific setting, a specific workflow, and a specific professional configuration. While this relational ontology has analytical and methodological consequences, it likewise contributes to the reshaping of how core concepts and values in AI research are intended and interpreted. Four concepts central to current AI debates are worth setting out in TAN terms before the assessment framework that operationalises them is fully introduced.

Among these values, explainability has received particular attention in the literature on AI in healthcare. The dominant framing in explainable AI (XAI) research treats explainability as a technical property of the model, addressable through visualisations, saliency maps, or confidence measures (Ananny & Crawford, 2016; Selbst et al., 2019). Recent critical work has questioned the practical adequacy of this framing for healthcare. Ghassemi et al. (2021) argue that current XAI approaches offer false hope when they assume explanations can be technically delivered to users without attention to the conditions under which explanations become meaningful. Gerdes (2024) shows that the practical role of explainability in medical decision-making depends on the institutional and professional conditions through which explanations are received, contested, and acted on, and ties explainability closely to the related values of trust and accountability. Amann et al. (2020) argue similarly for a multidisciplinary approach to explainability in healthcare AI. These critiques advocate for an approach that examines explainability empirically as a situated arrangement, attending to who needs an explanation, when, in what form, and with what consequences for responsibility and clinical action. In a TAN reading, explainability is a situated arrangement of visibility and responsibility. It concerns when an output appears, to whom, and with what consequences for authority, escalation, and accountability. Whereas mainstream XAI research treats explainability as a technical property of the model, from a TAN perspective, what counts as a useful explanation depends on the workflow moment, the professional role of the person encountering the output, and the temporal conditions of the work. Explanations are produced through socio-technical practice. They are not added to AI systems as technical features or treated as abstract, universal values.

In this light, the value alignment (VA) problem gains relevance (Gabriel, 2020). The VA problem is often framed as the challenge of imbuing AI systems with moral values aligned with some privileged set of ethical principles and standards. While mainstream AI research, primarily in computer science, often discusses value alignment as a property of the system's design and training that can be specified before deployment (Peterson, 2018; Russell, 2019), in a TAN reading, value alignment re-emerges as a continuous negotiation that unfolds through the AI integration process in its entirety. The values that matter, in specific contexts and for specific stakeholders, are not given in advance. They emerge from the underlying socio-technical investigations (Kudina & van de Poel, 2024). Values guiding implementation work meaningfully emerge through the staging of workflow change, the redistribution of responsibility, and the institutional arrangements that determine whether and how a technology enters clinical practice. The *Alignment* phase of the *AI in PRACTICE* framework (Section 4.3) operationalises this idea by making the negotiation explicit and testable, and by producing pilot scaffolds and provisional success criteria that allow stakeholders to see what they are committing to before full implementation of the AI solution takes place.

Accordingly, trust in our TAN reading is a relational property of socio-technical arrangements. Whereas mainstream AI research often treats trust as an attitudinal property of users towards the system (Glikson & Woolley, 2020; Asan et al., 2020), in a TAN reading trust depends on who has to act on the output, who can challenge it, and what the system demands from the clinical staff under conditions of shiftwork, interruptions, and time-critical care. This interpretation aligns with recent work in AI ethics that distinguishes trustworthiness from trustability as two

different conditions for trustworthy AI (Jannel & Tallant, 2025). Trustworthiness concerns whether an AI system, or the institutions deploying it, merits trust by being reliable, fair, and accountable (Reinhardt, 2022), as also reflected in the high-level framing adopted by the European Commission's Ethics Guidelines for Trustworthy AI (European Commission: Directorate-General for Health and Food Safety, 2019) and the subsequent White Paper on AI (European Commission, 2020). Trustability is the prior question of whether a given AI entity is even the kind of thing to which interpersonal trust can coherently apply, as opposed to mere instrumental reliance. From this perspective, trust in AI systems is best understood in relational terms, with attention directed toward the human and institutional arrangements that govern or participate in AI systems' design, deployment, and implementation. Trust, as trustability, in this reading, is maintained, strained, or refused at specific moments in the workflow. It is closely tied to how the interpretive burden is distributed across the professionals and stakeholders involved in the integration work, including clinical users, the implementation team, hospital management, IT, and developer-side staff. Trustability is a transversal topic across all phases of the *AI in PRACTICE* framework.

The TAN reading of accountability is best captured by the concept of distributed responsibility. Following Elish (2019), distributed responsibility refers to the way responsibility for outcomes is shared across multiple human and non-human actors in socio-technical systems, with the consequence that no single actor carries full accountability when things go wrong. By non-human actors we mean the technologies, infrastructures, protocols, and material arrangements that participate in shaping outcomes alongside human agents, including AI systems and their outputs, imaging infrastructure such as PACS, regulatory categories, and the documentation practices through which decisions are recorded. From a TAN perspective, distributed responsibility becomes visible only when the workflow is examined in its actual configurations, since distribution patterns vary by clinical setting, by professional role boundaries, and by how AI outputs are timed and presented. The conditions under which an AI system's operations become accessible to scrutiny, contestation, and correction are part of the same socio-technical fabric (Kitchin, 2014). They depend on the institutional channels through which outputs are interpreted, the documentation practices that record how decisions were made, and the workflow arrangements that determine who is in a position to challenge an output. The *Workflow Contextualisation* phase of our framework (Section 4.2) traces how AI tools interact with the distribution of responsibility already at work in clinical practice, and where the introduction of a new tool may shift that distribution. Throughout this article, when accountability is discussed in relation to AI integration, this is the TAN reading the term carries.

Two further commitments follow from this relational ontology and shape the TAN-oriented methodology underlying the *AI in PRACTICE* framework directly. The first is that AI integration is iterative. If the properties that matter are produced through relations, then understanding those properties takes time. A single moment of assessment, whether pre-implementation or post-implementation, cannot capture how a technology is being reshaped by the conditions it encounters. Preparatory work begins early and remains open to revision as the project moves through workflow contextualisation, staging, piloting, and assessment. Each phase produces artefacts that are carried into the next, and each phase can also produce reasons to revisit earlier decisions.

The second commitment is that participation happens from within practice. In the HTA tradition, stakeholder involvement typically operates through external consultation. Experts are brought in to assess the technologies to implement, patients are consulted about their preferences, and clinicians are surveyed about their degree of acceptance in existing workflows. Our TAN-oriented framework treats participation differently. Participation is a continuous and proactive working relationship with the clinical staff whose work spheres the AI technology will enter, the implementation team coordinating the integration, and the developer-side staff

producing and adjusting the technology. It is substantive, in the sense that clinician feedback can and does reshape the design, the pilot, and the assessment. It is distributed across time and across roles, because the conditions under which a technology becomes workable sit with different actors at different stages of the work. Co-creation in this reading refers to the collaborative process through which clinical users, the implementation team, and developer-side staff jointly shape, test, and adjust the technology in its actual setting of use. The design takes form through the encounter. It is not delivered for adoption.

3 EMPIRICAL BASIS: THREE AI IMPLEMENTATION PROJECTS IN RADIOLOGY

The empirical material in this article comes from a doctoral research project carried out at Aalborg University (Nielsen, 2026), whose fieldwork shows how the *AI in PRACTICE* framework took shape through recurring socio-technical situations across three radiology-facing AI projects. The doctoral project, like this paper, rests on a central working hypothesis: that AI integration in radiology clinics can be approached through five sequential stages. This article draws selectively on empirical situations from these projects to show how the phases look in practice. The full empirical analysis is developed in Nielsen (2026). The three projects followed successive stages in the development, clinical assessment, and pilot implementation of an AI-based imaging decision-support system used in brain MRI workflows.

The empirical material combines observations of clinical work, participation in project and protocol meetings, workshops and pilot feedback sessions, semi-structured interviews, and document analysis across several Danish hospital sites and collaboration settings involving clinicians, radiographers, researchers, and technology developers. Across the three projects, the dataset includes approximately 30 hours of observed or recorded meetings, 65 hours of in-situ clinical workflow observations, six semi-structured interviews, multiple workshops and pilot feedback sessions, and a corpus of more than fifty internal documents, including presentations, pilot plans, regulatory materials, and project documentation.

The *first project* (2019 to 2024) examined early collaboration processes and exploratory implementation activities related to the initial versions of the technology at an acute, stroke-ready university hospital. The work formed part of a regional innovation collaboration between clinicians, hospital innovation units, IT departments, and developers exploring how AI-based image analysis could be integrated into existing MRI workflows. Data collection included approximately 13 hours of participant observation in cross-organisational coordination meetings, where stakeholders discussed pilot scope, governance arrangements, workflow implications, and technical infrastructure such as PACS connectivity and server setup. This was complemented by approximately 45 hours of *in-situ* workflow observation across neurology and radiology departments, documenting routine coordination practices, documentation work, and the temporal organisation of stroke-adjacent imaging workflows across weekday and weekend shifts and across day and evening shifts. Six semi-structured interviews with radiographers, radiologists, neurologists, and innovation staff elicited reflections on responsibility, practical constraints, and the anticipated implications of introducing AI-supported image analysis.

The *second project* (January 2024 to January 2026) focused on preparing a prospective clinical study evaluating a next-generation version of the technology at a tertiary hospital stroke centre. This phase shifted the work from exploratory collaboration toward formal clinical assessment and protocol development. Empirical material from this project was generated through participation in more than fifteen study planning and protocol meetings, including steering group discussions and technical coordination sessions involving clinicians, researchers, and industry representatives. These meetings addressed study design, ethical approval procedures, regulatory considerations, and the technical integration of the AI system within existing imaging

infrastructure. This was complemented by approximately 15 hours of in-situ workflow observation conducted over multiple site visits during study preparation, focusing on imaging routines, handovers, and decision-making practices relevant to the planned clinical assessment.

The *third project* (March 2024 to February 2025) examined the development and pilot testing of a prototype embedded directly on the MRI scanner console as part of a product development collaboration. Planning activities began in March 2024, followed by a pilot phase running from June 2024 to February 2025 in a clinical imaging department. Empirical material from this phase consisted of preparation meetings, assessment workshops, and pilot feedback sessions with clinicians, radiographers, and technical staff involved in testing the system in practice. Approximately five hours of workflow observation documented how the prototype interacted with existing scanning routines and decision-support practices.

The analysis followed an abductive strategy, moving iteratively between field material and the TAN re-interpretations of core concepts in AI research such as explainability, trust, and accountability. Meeting notes, observations, interviews, workshops, and project documents were compared across the three projects to identify recurring socio-technical frictions concerning workflow fit, visibility, responsibility, and assessment criteria. These recurring patterns were used to validate and refine the phases into the form they take in this article. Three refinements are worth naming. What was initially called "Action and Review" became "Alignment (as Staging and Negotiation)". The staging element turned out to be analytically central, and alignment emerged as continuous negotiation rather than a single decision. What in the beginning was called "Implementation Monitoring" became "Co-creative Implementation". The relational and participatory dimension was what held pilots in place. The Preliminary Lead-in phase, which initially was treated as a mostly legal-technical prelude, expanded into a substantive phase of scope and legitimacy negotiation. All sites and participants are anonymised, and no patient-identifiable data are reported.

4 AI IN PRACTICE: THE PHASES

AI in PRACTICE unfolds through five phases (see Figure 1). Each phase addresses a different aspect of AI adoption, assessment, and integration, and each produces artefacts that carry into the next phase. The phases are: Preliminary Lead-in stage, Workflow Contextualisation, Alignment (as Staging and Negotiation), Co-creative Implementation, and Assessment and Empowerment.

1. **Preliminary Lead-in stage:** Attends to the organisational context in which an AI system may be introduced, including relations of hierarchy, responsibility, and decision-making in the hospital setting. Typical artefacts include a statement of work or pilot agreement, preliminary success concerns, and a governance pathway.
2. **Workflow Contextualisation:** Examines the existing clinical workflow through rapid ethnographic observation and qualitative interviews. Typical artefacts include technical milieu maps, relation maps, and hierarchy and workflow diagrams.
3. **Alignment (as Staging and Negotiation):** Stages prospective arrangements for how the AI would enter the workflow, who encounters it when, and what escalation paths apply. Typical artefacts include a pilot scaffold, visibility rules, and provisionally negotiated success criteria.
4. **Co-creative Implementation:** Moves the staged arrangement into pilot use, with iterative adjustments shaped by user feedback. Typical artefacts include a qualitative feedback overview, implementation change requests, and revised configuration.

5. **Assessment and Empowerment:** Reviews pilot results, clarifies interpretations, and discusses organisational implications. Typical artefacts include an assessment summary, recommendations to scale, stop, or modify, and an updated interpretation of success concerns.

Across all five phases, the framework treats drop-out as a legitimate outcome. If stakeholders judge that conditions cannot be made workable, that the technology does not fit local needs, or that the institutional arrangements cannot accommodate the integration, the work may be halted, redirected, or terminated. Drop-out is most explicit during the alignment phase (Section 4.3), where the staged configuration may serve as a justified termination point, and during the assessment phase (Section 4.5), where recommendations may include stopping the integration. In a recent paper, Nielsen et al. (2026) name the first three phases collectively as *anticipatory infrastructuring*.

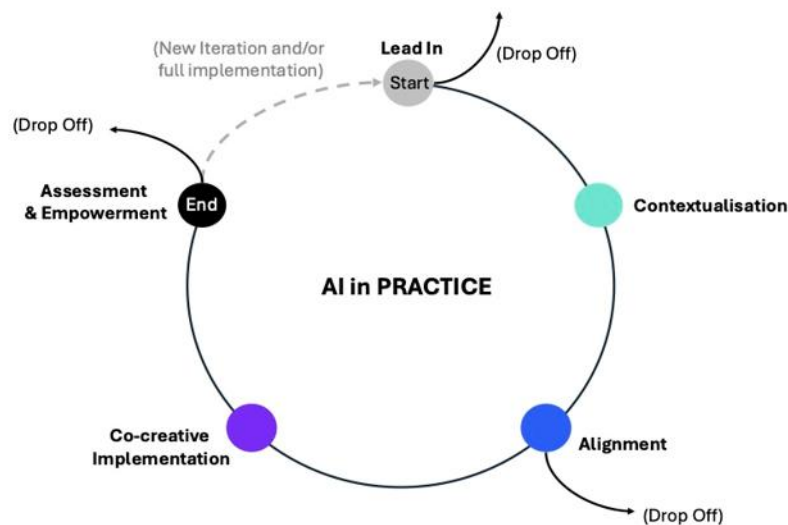


Figure 1: The AI in PRACTICE framework

AI in PRACTICE does not directly include patients as participants, since the framework focuses on the implementation work that happens upstream of the patient encounter. Patient interests enter the framework through clinical decisions, regulatory categories, and the workflow conditions under which AI outputs are interpreted and acted on. The framework does not include patients through direct consultation. This orientation accommodates the participatory design (Kanstrup & Bertelsen, 2013; Kanstrup et al., 2017) and action research (Thorsen & Børsen, 2018) traditions within TAN.

Before describing the phases in detail, it is worth specifying *who* carries out the work the framework requires. The *AI in PRACTICE* framework is designed to be used by an implementation team that includes someone with qualitative research experience. The competence can be placed in several different roles. The most natural locations are hospital innovation departments where these exist, or, where they do not, procurement units or medical technology project managers with qualitative training. On the developer side, the competence can be anchored in project managers or customer success staff who work closely with clinical partners. There is growing recognition in the implementation literature that AI integration benefits from this kind of dedicated capacity. Hospital innovation labs and similar units have been documented as productive sites for digital health implementation work because they bring together clinical, technical, and organisational perspectives in one team (Edelman et al., 2025). Studies of digital health transformation in hospital organisations identify analytical and project management capacity in the implementation team as one of the conditions for institutional readiness (Cresswell et al., 2024).

The framework is intended to be useful on both sides of the procurement relationship. Hospitals can use it to structure AI integration work and to articulate what they need from technology developers. Developers can use it to shape how their staff engages with clinical partners. When both sides bring this orientation, co-creation becomes a shared practice rather than something one side has to carry alone. Clinicians participate substantively in workflow contextualisation, alignment workshops, pilot adjustment, and assessment. Hospital management, IT, governance representatives, and developer-side staff participate at the points where their expertise and authority are needed. The implementation team holds primary responsibility for producing and maintaining the framework's artefacts, including technical milieu maps, relation maps, pilot scaffolds, and negotiated success criteria. The team also coordinates the inquiry and staging activities across the five phases.

To make the empirical grounding of the five phases explicit, Table 2 maps the main parts of our qualitative corpus across Projects 1-3 to the corresponding phases of the *AI in PRACTICE* framework. The aim is to show how the phases were developed and refined through recurring empirical situations, meetings, workshops, observations, and assessment activities in which the specific conditions for explainability, trust, accountability, and workflow fit were *negotiated* in practice. Each project did not follow all phases in the same sequence. It is important to note that the five phases were iteratively stabilised through recurring empirical situations in which similar socio-technical problems reappeared in different configurations across Projects 1-3.

Table 2: Map of empirical contributions to each phase.

Phases	Primary empirical material	Contribution	Typical output or developed item / artefact
<i>Phase 1: Preliminary Lead-in Stage</i>	Project 1: recurring lead-in / planning meetings with clinical leads, innovation/management actors, IT/regional actors, and developers; negotiations about pilot scope, governance boundaries, and legal/organisational constraints (e.g., Data Protection Agreements, access rights).	Shows how “value,” “evidence,” and “success criteria” are institutionally defined before any workflow change, and where early accountability and interpretive responsibility begin to crystallise (including what counts as acceptable justification and which actors must sign off).	Statement of work or pilot agreement; early success concerns; preliminary governance pathway; stakeholder commitments.
<i>Phase 2: Workflow Contextualization</i>	Project 1: rapid ethnography / workflow observation across emergency neurology and radiology, including day/evening and weekday/weekend rhythms (~45 hours); workflow-mapping interviews with radiographers, radiologists, neurologists; identification of existing technologies and handovers.	Grounds socio-technical entanglement in actual work by showing where AI outputs would appear, who is present, what time pressure looks like, and what interpretive resources are available (expertise, artefacts, handovers). Makes workflow constraints visible as empirical features of the work.	Technical milieu maps; relational complex maps; hierarchy and workflow diagrams; baseline descriptions of workflow moments and decision points.
<i>Phase 3: Alignment (Staging and negotiation)</i>	Project 1: protocol meeting where governance classification is negotiated (e.g., device-testing vs workflow change) and where “feasibility” is reformatted by institutional pathways; Project 2: protocol discussion where clinicians worry that a simplified “red/green” signal may bias attention and insist on controlling when to see the screen; Projects 1-2: workshops	Makes staging and negotiation visible: alignment emerges through disputes about legitimacy, bias, visibility, responsibility, and evaluation design. This is the phase in which explainability-as-practice becomes especially clear: what an “explanation” is allowed to do, when it is allowed to appear, and how it redistributes authority.	Pilot scaffold or future-imaginary concept artefact; provisionally negotiated success criteria; visibility rules (who sees what, when); escalation logic.

	debating blinding/influence and how AI presence reorders attention/authority.		
<i>Phase 4: Co-creative Implementation</i>	Project 3: pilot activities and iterative configuration; changes prompted by observed friction (e.g., manual activation creating cognitive load → auto-start feature); training and feedback loops; adjustments to how outputs are presented (interface/overlay and workflow placement). Project 1: planning discussions about managing downstream effects (e.g., avoiding “panic calls,” ensuring outputs support confirmation/rejection rather than disruption).	Shows how seemingly small frictions become redesign requirements, and how interpretive burden is materially shaped by interface, infrastructure, and training. This phase demonstrates that explainability is tuned through practice. It is not 'delivered' once	Qualitative feedback overview: implementation change requests; updated training practices; revised configuration or integration approach.
<i>Phase 5: Assessment & Empowerment</i>	Project 3: pilot evaluation material showing “plug and play” usability alongside decisive workflow constraints (e.g., 3-6 minute waiting bottleneck in short protocols; demand for much faster turnaround in acute timelines; reframing the tool as primary support vs conditional backup); evaluation workshop discussions translating explainability into concrete interface proposals (e.g., overlay vs arrows; list clarity; visibility timing).	Makes “value” empirical and negotiable by showing that what counts as benefit depends on time, infrastructure, and role boundaries. Accuracy alone does not determine it. It also shows explainability being judged through workflow consequences, including whether it reduces uncertainty or relocates burden through waiting time and extra interpretive work.	Evaluation summary: recommendations to scale, stop, or modify; prioritised change requests; updated interpretation of success concerns and accountability arrangements.

4.1 PRELIMINARY LEAD-IN STAGE

The preliminary lead-in phase establishes the organisational conditions under which an AI system may be introduced. It attends to the hospital’s hierarchy, responsibilities, and decision-making structures (see Figure 2), and begins by examining how the proposed value of the technology is articulated, by whom, and in relation to which clinical and institutional concerns.

From a TAN perspective, this early engagement is not preparatory background work but a constitutive part of implementation itself: it is where the project’s framing, assumptions, and conditions of justification first take shape. Across the three projects, this phase was enacted through recurring lead-in meetings in which stakeholders negotiated pilot scope, governance boundaries, and early success concerns before any workflow change was attempted. In Project 1, for example, these meetings surfaced assumptions about what explanations regulators, clinicians, and administrators would expect before AI could enter clinical work. Comparable patterns appeared in Projects 2 and 3, where early discussions produced high-level success criteria, stakeholder commitments, and, in many cases, a pilot agreement that recorded provisional responsibilities and expectations. These artefacts made explicit how the project was being framed at the outset and provided reference points for later phases.

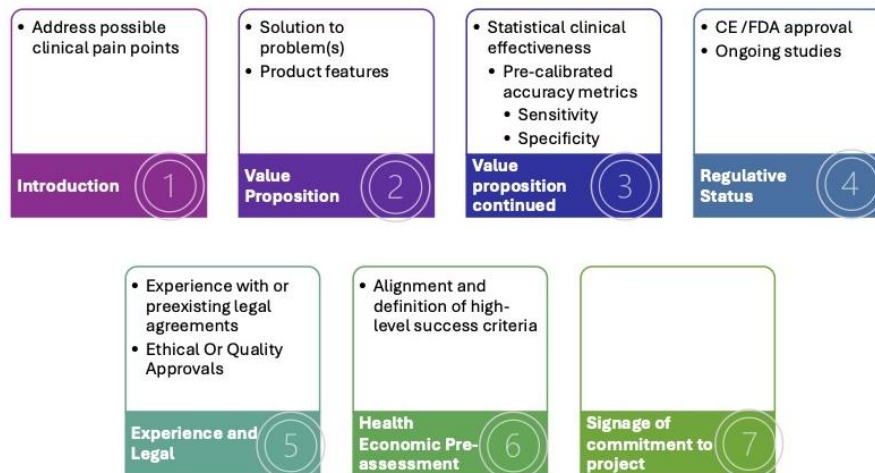


Figure 2: Lead-in negotiations starting the AI integration.

Phase 1 brings together three groups: the implementation team, hospital management, and the technology developer. The implementation team facilitates the negotiations, surfaces stakeholder assumptions, and documents how the project is being defined. Hospital management contributes the institutional perspective on whether the proposed deployment aligns with clinical priorities, infrastructural conditions, and resource constraints. On the developer side, sales or customer success staff typically participate early on, articulating the product's value proposition and indicating what the company can offer; as discussions move toward concrete pilot planning, project management staff take over to coordinate the technical and organisational arrangements required. The composition shifts as the phase progresses, but the lead-in work depends on all three groups being engaged from the start.

The steps in this phase synthesise recurring agenda patterns observed across the projects. Developers often begin by presenting a value proposition linked to locally identified needs, describing product features and anticipated clinical impact, often with reference to measures such as sensitivity and specificity. These claims are then related to local clinical concerns, regulatory standing (e.g., CE marking, FDA clearance, ISO 13485 compliance), and prior deployment experience. Discussions may also touch on preliminary health-economic considerations, depending on how participants relate the proposed project to clinical priorities and resource constraints. These exchanges make visible how stakeholders define the project's scope, expectations, and conditions of justification.

The importance of this phase is easy to underestimate. Many existing assessment frameworks, including MAS-AI, place value articulation, success-criteria negotiation, and regulatory clarification later in the process, once a technology is already being tested. In practice, across all three projects, these negotiations happened first and shaped every subsequent decision. When lead-in work is skipped or compressed, regulatory ambiguity surfaces during piloting, implicit success criteria diverge, and responsibilities for interpreting AI outputs remain unresolved until too late. Lead-in work is not a trivial prelude: it is where the project is configured. Skipping it does not save time; it defers critical decisions to phases less equipped to make them.

In these early negotiations, the institutional terms for explainability, accountability, and trust were already being configured. Stakeholders specified what counted as acceptable evidence, what outputs needed to be visible in existing systems, and who would carry interpretive responsibility once the tool entered clinical work. These same discussions shaped accountability arrangements, who would be answerable for AI-supported decisions, and the infrastructural and professional conditions required for clinicians to trust and act on AI outputs under time

pressure. These concerns did not enter the project as later topics to be addressed; they were foundational elements shaped through the institutional decisions made in the lead-in meetings, and the artefacts produced at this stage carried those configurations into the next phases.

4.2 WORKFLOW CONTEXTUALISATION

The workflow contextualisation phase examines the existing clinical workflow through rapid ethnographic observation and, where possible, qualitative interviews. Its purpose is to understand how clinical work is organised in practice, including how responsibilities, technologies, and institutional logics interact. Rapid ethnography is central to TAN-oriented work on health technology integration (Botin et al., 2015a, 2015b). It is the method that makes the relational ontology described in Section 2 operational. Without this empirical grounding, claims about how AI tools become workable in practice remain theoretical. With it, the implementation team can analyse the situated conditions that shape AI integration in ways that existing HTA frameworks cannot.

Across the projects, this phase was enacted through observations and workflow-mapping interviews in Projects 1 and 3. These covered radiology and emergency neurology work across shifts, weekdays, and weekends. The empirical work showcased how social and technical elements are entangled in practice, how existing technologies are used, and how heterogeneous human and non-human actors are coordinated in everyday work. The implementation team conducted these inquiries alongside clinicians, using established ethnographic methods adapted to ongoing socio-technical design, implementation, and assessment work.

Through these methods, the implementation team makes visible the roles, responsibilities, interaction dynamics, and local conditions that will shape how an AI system is later introduced. The same work identifies where explanations are needed in the workflow, who expects them, in what form, and for which decisions. It also traces how distributed responsibility, discussed in Section 2, is already at work in clinical practice and where introducing AI may shift that distribution. The scope of this phase can be adjusted to available resources. When ethnographic observation is not feasible, parts of the mapping can be carried out through workshop formats, provided that relevant stakeholders are represented. In these cases, the implementation team produces artefacts such as technical milieu maps, relation maps, and hierarchy and workflow diagrams. These artefacts make visible where AI outputs would appear, what interpretive resources are available at those moments, and where additional explanation may introduce friction or shift responsibility.

When this collective reconstruction is skipped or compressed, several problems tend to arise. AI tools are placed where developers assume the work happens rather than where it actually happens. Outputs appear at the wrong time or in the wrong system. Hidden coordination work, such as informal handovers, running phone calls, and parallel processes, only surfaces during piloting, where it appears as friction that clinicians and the implementation team must absorb. Professional roles and accountability lines become flattened, with the AI tool treated as if it interacts with a single user, even when it meets a configuration of users with different responsibilities and time pressures. The technical milieu maps and relation maps needed for Phase 3 are then missing or incomplete, forcing alignment work to proceed from a partial picture. These are not merely technical issues. They arise when workflow understanding is treated as something that can be assumed rather than reconstructed with the people who do the work. It is this reconstruction that makes the actual preconditions of AI integration visible.

4.3 ALIGNMENT AS STAGING AND NEGOTIATION

The alignment phase builds on the workflow examination and focuses on how alignment among stakeholders on values emerges through situated staging, negotiation, and translation work. Here, ‘staging’ refers to the process of setting up, preparing, or organizing an environment for an event or transition. In current AI debates, value alignment is often treated as something that can be specified in advance through system design and training. From a TAN perspective, value alignment is instead understood as a continuous staged negotiation that unfolds throughout the integration process. The implementation team facilitates this work, while clinicians, hospital leadership, IT and governance representatives, and, when relevant, developer-side staff contribute the perspectives, constraints, and concerns that shape what alignment can mean in this setting. AI outputs, infrastructures, and regulatory categories also act in this process, since they constrain what arrangements are possible. The values that matter are not predetermined. They emerge, are contested, and become stabilised through the staging of workflow changes, the redistribution of responsibility, and the institutional arrangements that determine how a technology enters clinical practice. This phase is where contextually meaningful values come into focus as practical objects, and where the artefacts that record them, such as pilot scaffolds (see Figure 3), visibility rules, and negotiated success criteria, are produced.

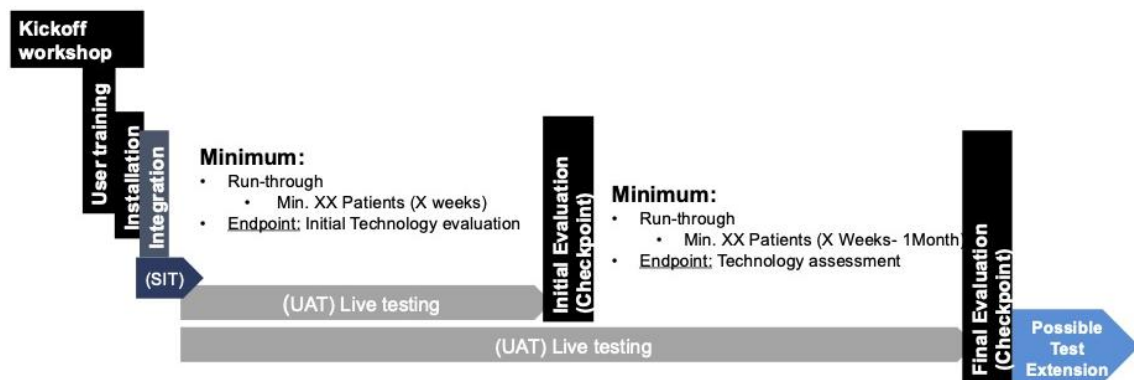


Figure 3: Pilot Scaffold example

Across Projects 1 to 3, this phase was enacted through concrete negotiation over governance categories, infrastructural dependencies, and temporal constraints. In Project 1, clinical and project stakeholders encountered a governance ambiguity that could not be resolved through planning alone. The same proposed pilot could be classified either as testing medical equipment or as a workflow change. This distinction shaped which institutional review pathway would apply, the administrative burden and cost of approval, and what kinds of documentation would be considered legitimate. The implementation team and the clinical and IT stakeholders therefore staged alternative pilot pathways, outlining different submission routes, timelines, and resource assumptions, and negotiated what kind of pilot would be feasible under each classification. The outcome was a provisional decision logic and a revised pilot scaffold that enabled the project to move forward while leaving the classification question institutionally open. Comparable dynamics emerged when infrastructural and temporal constraints became decisive. In Project 2, feasibility hinged on unresolved image-transfer dependencies, including where and how images could be routed within existing systems. The implementation team, together with IT and developer staff, initiated parallel technical tracks and negotiated responsibility between scanner configuration, PACS routing, and IT governance. In Project 3, short and time-critical protocols exposed system turnaround time as a workflow bottleneck. The implementation team and clinical staff renegotiated the AI's role, considering whether it should function as primary decision support in acute pathways or as a conditional backup tool activated

under specific staffing and coverage conditions. In each case, alignment was achieved by redistributing constraints across actors and infrastructures.

The work in this phase is highly performative. The implementation team collaborates with clinicians and other stakeholders to stage prospective arrangements, including who encounters the AI output, through which interface, with what escalation path, and with what accountability implications. They also negotiate what counts as a meaningful explanation in context. The aim is not to converge on a single optimal workflow. The aim is to surface frictions and stabilise a provisional configuration that can be tested, revised, or discontinued in subsequent phases. This staging and negotiation orientation is central to TAN-oriented technology assessment (Botin & Børsen, 2024).

These negotiations are complemented by structured participatory envisioning practices used in TAN-oriented technology assessment. The implementation team facilitates these practices, in which clinicians and other stakeholders articulate desirable and undesirable trajectories, interpret the social meaning of the AI system, and examine whether the emerging configuration aligns with clinical values and institutional mandates. By integrating future imaginaries into ongoing negotiations, the phase supports the articulation of provisionally negotiated success criteria for piloting and assessment. Within this phase, explainability becomes a design and governance question. In these workshops, clinicians articulate what should be explained, to whom explanations should be addressed, and what level of explanation is sufficient under conditions of time pressure and professional accountability. These negotiations redistribute interpretive burdens across the workflow and shape both interface design and responsibility structures in practice. Figure 5 illustrates a pilot scaffold that captures these negotiated arrangements.

The phase typically begins with a workshop facilitated by the implementation team, in which artefacts from the workflow examination are presented to a cross-professional project group within the hospital. This group includes representatives from radiology, neurology, radiography, nursing, and relevant managerial levels. The workshop functions as a site of collective interpretation. Preliminary findings are contested, refined, and translated into prospective pilot configurations. The workshop does not seek consensus for its own sake. It surfaces disagreements and clarifies under what conditions the AI technology is considered workable. If the technology is judged unlikely to provide contextually meaningful value, the phase may result in a formal change request to the developer or serve as a justified termination point. Alignment as staging and negotiation, therefore, functions as both a stabilisation and a filtering mechanism. Its primary output is a future imaginary concept artefact or pilot scaffold that renders the negotiated configuration explicit and testable, making continuation, modification, or discontinuation an informed and collectively articulated decision. As seen across Projects 1 to 3, explainability becomes a matter of when an output should be seen and by whom. Clinicians expressed concern that a simplified traffic-light style signal could bias attention and, therefore, treated access to the screen and visibility timing as a negotiable governance decision rather than a simple interface preference. The contextually meaningful values that emerge in this phase are then carried into the next phase, where they are tested against pilot use and adjusted in response to user experience.

4.4 CO-CREATIVE IMPLEMENTATION

The co-creation and piloting phase begins once the previous phase is deemed successful and implementation is agreed upon. This phase moves the project into a hands-on stage, similar to the realism and implementation phase in the future workshop methodology (Jungk & Müllert, 1987), which is widely used in TAN-oriented studies and participatory design work in healthcare. Co-creation refers to the collaborative process through which clinical users, the implementation team, and developer-side staff jointly shape, test, and adjust the technology in its actual setting

of use. The design takes form through the encounter rather than being delivered for adoption. This phase focuses on transforming the values and imaginative ideas from the previous phase into working agreements involving user training, technology piloting, and continuous assessment. The implementation team coordinates the pilot setup with hospital partners and developer-side staff, while clinical users engage directly with the new technology and contribute the experiential and workflow knowledge that the iteration depends on.

The contextually meaningful values identified in Phase 3 are further challenged and negotiated as users encounter concrete issues and specific role-based needs. Users' experiences, feedback, and recommendations, gathered and analysed by the implementation team, become the basis for iterative improvement. Across the projects, this phase was enacted through situated adjustments and iterative negotiation. In Project 3, early pilot use surfaced a friction that the implementation team observed *in situ* and that radiographers articulated explicitly. Manual activation created avoidable cognitive load. The implementation team relayed this to the developer, who introduced an auto-start feature and related workflow adjustments. Comparable dynamics appeared in other projects, where early pilot encounters surfaced practical constraints that could not be anticipated in advance. These included the timing of AI outputs, the visibility of results within existing systems, and the distribution of interpretive responsibility across clinical roles. Each of these issues required negotiation among clinical users, IT staff, and developer-side personnel, and each resulted in adjustments to the pilot configuration.

The implementation team uses observational studies and semi-structured interviews in this phase to examine how the technology is used and revised in a clinical setting. Practical questions addressed collaboratively include defining a pilot period suited to the site's conditions, deciding whether the pilot should be longitudinal or alternating in design, determining which clinical users to include and how to organise their participation, clarifying any interventional components in the technical setup or protocol, identifying required approvals, and specifying data collection methods, feedback loops, and assessment points. These components are developed collaboratively, with the implementation team coordinating across hospital innovation, IT, and clinical departments and developer-side staff. This allows the pilot setup to reflect insights generated during Phase 2 and the values that emerged in Phase 3.

The implementation team facilitates the iterative feedback and adjustment process, working with clinical staff and other stakeholders to make visible the practical challenges, revisions, and negotiations that emerge as the technology becomes part of everyday clinical work. The team produces a qualitative feedback overview summarising user experiences, workflow frictions, and implementation adjustments. This material informs the assessment of the pilot and the technology in the final phase. Iterative piloting also illuminated how clinicians engage with AI-generated outputs in real scenarios, including when explanations are sought, accepted, ignored, or contested. This provides insight into the practical relevance and burden of explanation. During piloting, explainability is tuned through situated adjustments to interfaces, training routines, and infrastructure. The implementation team coordinates between clinical users who articulate what is needed and developer-side staff who implement the adjustments, so that what the system communicates can be worked with under time pressure and shift work conditions.

When this phase is skipped or compressed, several problems tend to arise. Technologies might be deployed without sufficient adjustment to local workflow conditions, resulting in outputs appearing at the wrong time or in the wrong system, and users encounter friction that could have been resolved earlier. The implementation team will then be forced to absorb these issues at a later stage. The iterative adjustments that make the technology workable are then missing or incomplete, and the assessment phase proceeds from a partial picture. These are not merely technical issues. They arise when co-creation is treated as optional rather than as the practical

work through which the technology becomes usable in context. The co-creation and piloting phase is therefore essential for ensuring that the negotiated values and workflow arrangements from earlier phases are tested, revised, and stabilised in practice.

4.5 ASSESSMENT AND EMPOWERMENT

The assessment and empowerment phase reviews results, clarifies interpretations, and addresses organisational issues that have emerged during the implementation. It brings together the implementation team, clinical staff who participated in the pilot, departmental leadership, and, when relevant, hospital innovation or procurement representatives and developer-side staff. The implementation team facilitates a workshop that examines the technology's tangible benefits to the clinic, its suitability for broader use in the workflow, and how participants now understand the value articulated during the initial lead-in phase. The workshop also consolidates the user feedback and in-context assessment material gathered during Phase 4 and generates the assessment material needed for decisions about modification, continuation, or broader deployment.

Across the projects, this phase was enacted through structured assessment workshops and analysis of pilot data. In Project 3, clinical users described the embedded solution as intuitive and requiring minimal training, often referring to it as "plug and play." The implementation team's assessment work showcased a decisive socio-technical constraint that this framing concealed. In short, time-critical protocols, radiographers sometimes waited three to six minutes post-scan for results. This waiting time became a workflow bottleneck in acute timelines and reshaped how value and usefulness were understood in practice. Participants specified that inference time would need to drop below 30 seconds to fit stroke care timelines. The assessment also showed how small integration decisions shaped interpretive burden. Early manual activation created avoidable cognitive load, which led the developer to introduce an auto-start feature. Participants further translated explainability concerns into concrete interface proposals, such as replacing colour overlays with directional arrows to reduce visual stress and make prioritisation cues easier to work with. Comparable patterns appeared across Projects 1 to 3, where assessment tied explainability to model outputs, uncertainty, visibility, timing, and responsibility within the workflow.

This phase examines explainability empirically by drawing on artefacts and materials generated in earlier phases. The implementation team uses technical milieu maps that chart the technological environment of the clinical setting, relation maps that trace relations among stakeholders and technologies, hierarchy and workflow diagrams that visualise existing processes and possible changes in roles and coordination, qualitative feedback from workshops, semi-structured interviews, and observations that provide insight into user experience, and the success criteria and health economic considerations that became relevant to the value articulated during the lead-in phase. These materials allow the team and participants to analyse how the AI system became explainable in practice, including whether explanations contributed to understanding, decision confidence, and institutional accountability. As discussed in Section 2, explainability in TAN terms is not a technical property but a situated arrangement of visibility and responsibility produced through the workflow conditions in which AI outputs are encountered. The artefacts produced in earlier phases provide concrete points of reference for these discussions. The implementation team consolidates them into an assessment summary, prioritised change requests, and updated interpretation of success concerns and accountability arrangements. Together, these outputs form the basis on which the hospital and developer decide whether and how to scale, adjust, or discontinue the integration.

Beyond these decision-oriented outputs, the assessment phase can also have empowering effects on the participants involved. Empowerment in this framing is not a separate step. It refers to capacities and capabilities that the assessment process can surface and that

participants may carry forward beyond the immediate pilot. In our material, such effects appeared most clearly at the individual level, where clinical users described possible skill development and increased confidence in working with the technology. The framework can also support shared workflow understanding among professional groups engaged in workshops and may contribute to institutional capacity for future AI integrations, although these broader effects were not systematically evaluated in our three projects.

An illustrative example came from Project 3. In evaluation interviews, clinical users described the embedded AI tool as a possible "learning tool" and a "good training and teaching tool" for junior radiographers learning to recognise pathology over time. As one senior radiologist put it, the system was "useful especially for young and inexperienced technicians" and could provide "self-confidence" in settings where direct radiologist supervision was not always available. These descriptions point to an empowering potential at the individual level. They illustrate the kinds of effects that the assessment process can surface as part of evaluating what an AI tool means in practice, although they do not on their own constitute evidence that learning effects were realised or persisted beyond the pilot.

5 CONCEPTUAL AND ANALYTICAL INSIGHTS

The *AI in PRACTICE* framework, through its five-phase techno-anthropological inquiry-and-staging approach, examines how AI becomes workable, accountable, and meaningful in clinical practice. Across 3 Projects, the empirical material shows that integration is repeatedly achieved or blocked through negotiations over infrastructures, governance pathways, professional jurisdictions, and interface visibility. Technical properties of the tool are necessary but not sufficient for integration; the socio-technical conditions in which those properties operate matter just as much. The framework's contribution to human-technology relations research lies in specifying where to look and what to document when explainability, value alignment, and trust are enacted as situated socio-technical practices. The four insights that follow show what this specification produces in our material.

A first insight concerns explainability. In the dominant XAI framing, explanations are often treated as outputs that can be added to a system (visualisations, saliency maps, confidence measures). Our cases suggest that, in these clinical settings, explainability took the form of a 'situated arrangement' of visibility and responsibility: to recognise when an output appears, to whom, and with what consequences for authority, escalation, and accountability (similar claims in Amann et al., 2020; Ananny & Crawford, 2016; Elish, 2019). In Project 2, clinicians' concern that a simplified traffic-light signal could bias attention reframed explainability as a governance question about when the screen could be seen, not merely an interface preference. In Project 3, explainability was evaluated through its workflow consequences under time pressure: waiting time and turnaround became decisive in determining whether outputs could function as usable support or as a bottleneck. These examples show that explanations are staged, timed, and made consequential: Explainability was repeatedly judged through temporal fit and controlled visibility, with informational detail becoming meaningful only in relation to those conditions.

A second important insight concerns *value alignment*, which in our material emerged through *negotiation* across heterogeneous actors (clinical roles, IT infrastructures, protocol requirements, governance boundaries, and AI outputs). In Project 1, the governance ambiguity (device-testing vs workflow change) shaped what kind of pilot was even possible, and participants responded by staging alternative pathways instead of resolving the ambiguity abstractly. In Project 2, infrastructural dependencies and image-transfer routing similarly required parallel technical tracks and redistribution of responsibility. In these situations, alignment appeared as an effect of translation work and provisional stabilisation.

A third insight concerns *trust*. In our material, questions of trust were closely tied to socio-technical arrangements that organised the interpretive burden: who had to act on the output, who could challenge it, and what the system demanded of staff under conditions of shiftwork, interruptions, and time-critical care. In Project 3, the auto-start adjustment not only simplified the radiographer's workflow. It changed the conditions under which radiographers could trust the system to do the right thing without requiring constant attention. In Project 2, clinicians' insistence on controlling when to see the AI signal was a matter of trust, not just an interface preference. They were specifying the conditions under which the system's output could be received as informative rather than as a directive. This draws attention to the workflow situations in which trust is maintained, strained, or refused, and to the design and governance work that constitutes those situations.

A fourth insight concerns *accountability*. Across Projects 1-3, accountability took the form of *distributed responsibility* in practice. The institutional channels through which AI outputs are interpreted, the documentation practices that record how decisions were made, and the workflow arrangements that determine who can challenge an output, all shaped where responsibility could plausibly sit. In Project 1, the governance ambiguity over device-testing versus workflow change was not only a question of the pilot pathway. It also shaped which actors would be answerable for the deployment and through which institutional channels. In Project 3, the auto-start adjustment redistributed where interpretive burden sat between the radiographer and the system. These observations suggest that accountability for AI in healthcare is best understood as an arrangement of socio-technical conditions rather than as a property assigned to a single actor.

These four insights affect the cast of actors that the *AI in PRACTICE* framework engages, and the implications fall on them in different ways. For clinicians, the framework asks that they participate as interpreters of workflow conditions and as articulators of what counts as a meaningful explanation in their setting. For hospital management, the framework asks that they engage with the institutional negotiations through which value and accountability are configured early, before workflow changes are introduced. For IT and governance representatives, the framework asks that infrastructural and regulatory conditions be treated as objects of staging rather than fixed boundaries. For developer-side staff, the framework asks that pilot configuration and iterative adjustment proceed in partnership with clinical users, with the implementation team coordinating the exchange. Patients are not direct participants in this work, since the framework operates upstream of the patient encounter. Still, the conditions reconfigured by the framework shape how AI outputs become available and actionable in clinical practice, thereby affecting the quality and timing of the care patients receive.

As a result, the *AI in PRACTICE* framework operates differently from existing HTA models and is best understood as complementary, especially to MAS-AI. It does not replace MAS-AI as a checklist or decision model. Instead, it produces practice-based artefacts, workflow diagrams, technical milieu maps, pilot scaffolds, and negotiated success criteria that show how general assessment criteria are enacted, contested, and revised in context. Where HTA frameworks ask whether a system is safe, effective, and economically justified, the *AI in PRACTICE* framework foregrounds the socio-technical conditions that make those questions actionable: how infrastructures enable or constrain use, how timing reshapes value, and how situated explanations redistribute responsibility across professions. In this way, the framework can strengthen HTA processes by documenting how value, risk, and explainability are stabilised through integration rather than assumed in advance.

Similar *socio-technical problems* can recur across settings and project stages. Rather than presenting a single bounded application of all five phases, our narrative synthesises recurring empirical situations across Projects 1-3. This is a strength of the methodological articulation: it shows how the framework can identify *cross-cutting* patterns of negotiation and staging while

also clarifying the limits of what can be claimed in different circumstances. The framework should therefore be read as a *conceptually grounded*, empirically informed proposal and analytic lens for practice, not as proof that following the phases will produce specific outcomes. Future work could extend this contribution through comparative case studies across hospitals and AI use cases, including more systematic analysis of how particular artefacts, such as pilot scaffolds and negotiated visibility rules, travel, or fail to travel, between organisational contexts. Such work could also examine more closely how assessment models and regulatory categories shape implementation trajectories and the practical meaning of values such as explainability or trust in specific settings.

6 CONCLUSION

This article has presented the *AI in PRACTICE* framework as a *techno-anthropological* inquiry-and-staging approach for studying and supporting AI integration as a situated socio-technical accomplishment. The framework specifies five phases (Preliminary Lead-in, Workflow Contextualisation, Alignment as Staging and Negotiation, Co-creative Implementation, and Assessment and Empowerment) through which the implementation team, clinical users, hospital management, IT and governance representatives, and developer-side staff articulate, test, and revise what counts as valuable and what counts as a meaningful explanation in their setting. The empirical material across three projects supports the central argument of the paper that socio-technical conditions and relations that shape AI integration in healthcare belong at the centre of integration work and cannot be assessed only after implementation. These conditions and relations include infrastructural timing, interface visibility, professional role boundaries, governance classifications, and the organisation of interpretive burden under time pressure. They are produced within and across all five phases, and shape what needs to be assessed at the end.

The *AI in PRACTICE* framework thus well complements formal HTA models such as MTV, MAST, and particularly MAS-AI by examining the implementation work through which assessment categories become actionable in context, neglected so far by existing HTA models. By following the five-phase framework, *AI in PRACTICE* provides a procedure for assessing and implementing AI in clinical practice that takes into account the *socio-technical* specificities that typically complicate AI integration. *AI in PRACTICE* continues where MAS-AI stops. Together, they offer a comprehensive account of what AI integration requires in concrete clinical settings.

Data Access Statement

This research draws on qualitative, ethnographic data gathered through participatory implementation processes in clinical settings. Owing to the confidential and context-sensitive nature of this material, the data are not publicly available. Access may be granted by the corresponding author upon reasonable request, subject to institutional approvals and ethical considerations.

Contributor Statement

- Maria Bach Nielsen: Conceptualization, Methodology, Investigation, Writing (original draft), Writing (review and editing), Visualization, and Project administration.
- Tom Børsen: Conceptualization, Supervision, and Writing (review and editing).
- Martin Lillholm: Conceptualization, Supervision, and Writing (review and editing).
- Alessandra Cenci: Writing (review and editing).

Use of AI

During the preparation of this work, the authors used Grammarly and Claude (Anthropic) in order to make minor language and grammar improvements in the final stages of manuscript preparation. No generative

AI tools were involved in the intellectual or conceptual development of the article; the ideas, analysis, interpretations, and conclusions are the authors' own. After using these tools, the authors reviewed, edited, made the content their own and validated the outcome as needed, and take full responsibility for the content of the publication.

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Conflict of Interest Statement

M.B. Nielsen is a minority shareholder and employee of Cerebriu A/S. M.Lillholm is a minority shareholder and employee of Cerebriu A/S. T.Børsen has no conflict of interest/A. Cenci has no conflict of interest.

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