Embedding Responsibility in AI-Driven Transformation: A Study of Responsible Business Model Innovation in European Healthcare

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Dissertation written under the supervision of
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Abstract (EN)

Organizations are rapidly adopting artificial intelligence, but many still lack clear pathways to integrate responsibility for the AI-driven changes to their business models. This dissertation examines this research question: How do organizations implement responsible business model innovation when adopting AI? The study uses a qualitative, single instrumental case study design and is based on 15 semi-structured interviews conducted in the European health sector, a high-stakes environment characterized by the EU single market and strict regulatory expectations.

The findings suggest that AI-driven responsible business model innovation unfolds across four interconnected dimensions. Augmentation (leveraging AI for clinical and operational efficiency), Embedding (navigating systemic constraints like time scarcity and economic pressures), Legitimation (establishing governance, validation, and ethical oversight), and Reconfiguration (fostering systemic transformation in roles and care models). These dimensions constitute a practical framework for managers, highlighting actionable governance strategies and underscore the non-negotiable role of human oversight.

Across the case, the study surfaces a “responsibility paradox”, as external factors necessitate the adoption of AI, while internal constraints hinder responsible business model innovation. The dissertation concludes that responsible AI-supported business models emerge through continuous negotiation, not through a linear, straightforward implementation. Responsibility in this context is not added retroactively, but must be treated as a design principle from the outset and maintained through socio-technical governance and consistent human accountability in order to protect both innovation and societal legitimacy.

Keywords: Artificial Intelligence (AI); Responsibility; Responsible Innovation; Business Model Innovation; Responsible Business Model Innovation; Healthcare; European Union; Governance; Ethics; Case Study; Qualitative Research

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Sumário (PT)

As organizações estão a adotar a inteligência artificial, mas muitas ainda carecem de caminhos claros para integrar a responsabilidade pelas mudanças impulsionadas pela IA nos seus modelos de negócio. Esta dissertação examina a seguinte questão de investigação: Como é que as organizações implementam a Inovação Responsável do Modelo de Negócio ao adotar a IA? O estudo utiliza um desenho qualitativo de estudo de caso instrumental único e baseia-se em 15 entrevistas semiestruturadas realizadas no setor de saúde europeu.

Os resultados sugerem que a inovação responsável do modelo de negócios impulsionada pela IA se desenvolve em quatro dimensões interligadas. Aumento (aproveitamento da IA para eficiência clínica e operacional), incorporação (navegação por restrições sistémicas, como escassez de tempo e pressões económicas), legitimação (estabelecimento de governança, validação e supervisão) e reconfiguração (promoção da transformação em funções e modelos de cuidados). Essas dimensões fornecem uma estrutura para os gestores, destacando estratégias viáveis e enfatizando o papel inegociável da supervisão humana.

Ao longo do caso, o estudo revela um «paradoxo da responsabilidade», uma vez que fatores externos exigem a adoção da IA, enquanto restrições internas impedem essa inovação responsável. A dissertação conclui que modelos de negócios responsáveis apoiados pela IA surgem por meio de negociações contínuas, e não por meio de uma implementação linear e direta. A responsabilidade, neste contexto, não é adicionada retroativamente, mas deve ser tratada como um princípio de design desde o início, mantida por meio da governança e da responsabilidade humana consistente para proteger tanto a inovação quanto a legitimidade social.

Palavras-chave: Inteligência Artificial (IA); Responsabilidade; Inovação Responsável; Inovação do Modelo de Negócio; Inovação Responsável do Modelo de Negócio; Cuidados de Saúde; União Europeia; Governação; Ética; Estudo de Caso; Investigação Qualitativa

Título: Incorporar a Responsabilidade na Transformação Impulsionada pela IA: Um Estudo sobre a Inovação Responsável do Modelo de Negócio nos Cuidados de Saúde Europeus

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1 Introduction

Artificial Intelligence (AI) is transforming how organizations create, deliver, and capture value (Brynjolfsson and McAfee, 2017; Gibson, 2024; Singla et al., 2025), the technology enhances efficiency, enables novel products and services, and reshapes industry structures (Füller et al., 2022; Gibson, 2024). At the same time, AI adoption brings ethical, social, and governance challenges (Balcioğlu et al., 2025; Papagiannidis et al., 2025). Concerns related to fairness, transparency, accountability, and data governance reveal a widening gap between technological capability and responsible managerial practice (Balcioğlu et al., 2025; Butt, 2024; Papagiannidis et al., 2025). Therefore, if organizations want AI-supported innovations to be sustainable, they must align them with societal expectations, regulatory requirements, and ethical norms as an integral part and not consider these points as an afterthought (Balcioğlu et al., 2025; Stilgoe et al., 2013).

This tension reveals that, despite rapid progress in AI and digitalization, organizations often lack a coherent framework to integrate responsibility into their business models (BM), which is a crucial problem (Jorzik et al., 2024a). Business model innovation (BMI) research explains how firms reconfigure value creation, delivery, and capture in response to technological and environmental shifts (Foss and Saebi, 2018). In parallel, the literature on Responsible Innovation (RI) offers normative principles for guiding ethically and socially desirable innovation processes (Stilgoe et al., 2013). However, the integration of these two domains, conceptualized as Responsible Business Model Innovation (RBMI), remains theoretically and empirically underdeveloped (Magni et al., 2024). Likewise, while emerging work on Responsible AI (RAI) provides governance mechanisms for AI deployment, its connection to BM design and transformation is insufficiently theorized (Brynjolfsson and McAfee, 2017; Hope and Moehler, 2015; Jorzik et al., 2024b). As a result, organizations are left without clear guidance on how to structure AI-enabled BMI that is both ethically robust and societally legitimate (Füller et al., 2022; Jorzik et al., 2024a).

This dissertation addresses this gap by examining the following research question: How do organizations implement RBMI when adopting AI? This question is relevant to both academic and managerial audiences. For scholars, it advances understanding of how technological, ethical, and strategic dimensions jointly shape RI at the BM level. It contributes to bridging fragmented streams on BMI, RI, RBMI, and RAI, thereby clarifying how responsibility can be conceptualized not merely as a constraint but as a generative design principle (Lüdeke-Freund et al., 2024; Owen et al., 2013). For practitioners and policymakers, the topic is significant because organizations increasingly face regulatory pressures, stakeholder expectations, and operational risks associated with AI (Bocken et al., 2014; Butt, 2024; Kilian et al., 2025; Singla et al., 2025). The remainder of this dissertation is structured as follows. Section 2 reviews the literature on BMI, RI, RBMI, AI, and RAI. Section 3 details the qualitative case study methodology. Section 4 presents the study results, structured according to four dimensions. Section 5 discusses theoretical and practical implications. Section 6 concludes with key insights, limitations and future research. The appendices contain supporting figures, the interview guide, the full set of interview summaries and the data coding.

2 Literature Review

This study draws on established work in BMI and RI to examine how organizations integrate AI into responsible BM design. It builds on conceptualizations of BMs as activity systems governing value creation and capture (Teece, 2010; Zott et al., 2011) and on process-oriented perspectives of BMI as an organizational change phenomenon (Foss and Saebi, 2018; Zott et al., 2024). These foundations are extended through RI theory, which introduces ethical, social, and environmental considerations into innovation governance (Owen et al., 2013; Stilgoe et al., 2013). The review also incorporates RBMI research that frames responsibility as a strategic feature of BM architecture (Magni et al., 2024) and RAI as a governance framework for AI-enabled transformation (Papagiannidis et al., 2025). Taken together, these perspectives provide a knowledge base that can be built upon to analyze how AI acts as a catalyst for RBMI under conditions of increased societal and regulatory expectations.

2.1 Business Model Innovation

This section treats BMI as the central foundation for understanding how firms deliberately reconfigure value creation, delivery, and capture in response to technological and environmental change.

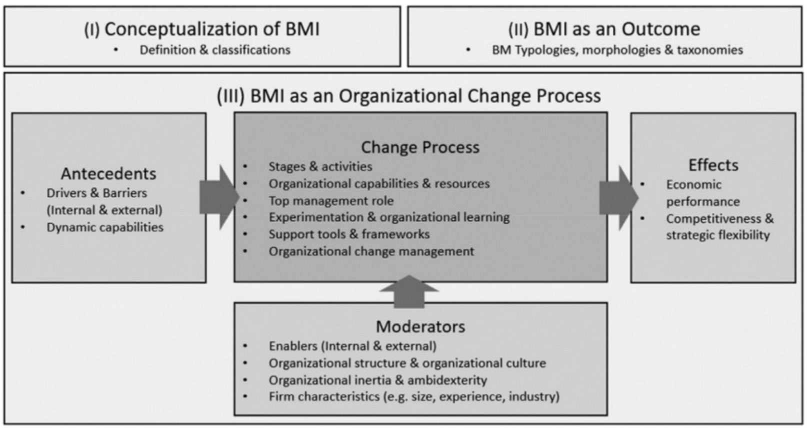
2.1.1 Core Concepts of Business Models

As a basis for BMI research, the following section first clarifies how a BM is defined. BM research has developed rapidly, particularly in response to technological change, but has long suffered from conceptual fragmentation (Foss and Saebi, 2018; Zott et al., 2011). Still, a broad consensus holds that the BM is a distinct unit of analysis that explains, at a system level, how a firm operates economically (Zott et al., 2011). At its core, the BM specifies a system of activities characterized by their content, structural interdependencies, governance across organizational boundaries (Zott et al., 2024, 2011), and an underlying value logic that explains value creation and capture (Foss and Saebi, 2018; Teece, 2010). In practical terms, the BM explains how an organization creates value for customers, induces payment, and turns revenues into sustainable profits (Teece, 2010). In this sense, the BM reflects management's underlying assumptions about customer needs, the mechanisms used to meet those needs, and the organizational logic required for economic viability (Teece, 2010).

A key feature of this perspective is its holistic character. Rather than a checklist of parts, a BM is a configuration of interdependent activities (Zott et al., 2024, 2011). These activities often span organizational boundaries and link firms with customers, partners, and other stakeholders (Zott et al., 2024). A key feature of effective BMs is the complementarity of activities, whereby changes in one element increase the value of other elements, which increases complexity and the difficulty of imitation and thereby creates a competitive advantage (Foss and Saebi, 2018). Overall, the BM functions as a firm-centric, boundary-spanning system that integrates strategic intent with operational execution and economic outcomes (Zott et al., 2011). To operationalize this high-level construct, frameworks such as the Business Model Canvas (BMC), depicted in Appendix A - Business Model Canvas, break the BM into nine building blocks, from customer segments to revenue streams (Fatima et al., 2021; Foss and Saebi, 2018). How such a BM can be innovated will be explained in the next section.

2.1.2 Conceptual Foundations of Business Model Innovation

Summarizing the main topics of past-and-current research, the BMI literature can be broadly structured into three complementary perspectives, which are synthesized in Figure 1 (Santa-Maria et al., 2021).



(Santa-Maria et al., 2021)

Figure 1. Business Model Innovation - Research based Framework

(I) Conceptualization of BMI. At this level, BMI is defined as designed, novel, and nontrivial changes to key BM elements and/or to the architecture linking them (Foss and Saebi, 2017). Two dimensions are typically used to specify the change. First, the degree of novelty ranges from innovations new to the firm to those new to the industry (Foss and Saebi, 2017). Second, the focus is on the scope, which ranges from modular changes affecting a single component to architectural or systemic changes that reconfigure complementarities across the entire system (Aagaard, 2024; Foss and Saebi, 2017).

(II) BMI as an Outcome. From an outcome view, research focuses on the observable BM configurations that result from innovation in value architecture (Foss and Saebi, 2017; Zott et al., 2024). Key typologies include industry model innovation (redefining or creating industry segments), enterprise model innovation (changing the firm's role and partnerships in the value network), and revenue model innovation (adapting value propositions and pricing logic) (Zott et al., 2024). One widely discussed outcome is the shift toward circular business models (CBM), which aim at regenerative value creation by slowing, closing, narrowing, or regenerating resource loops (Bocken et al., 2014).

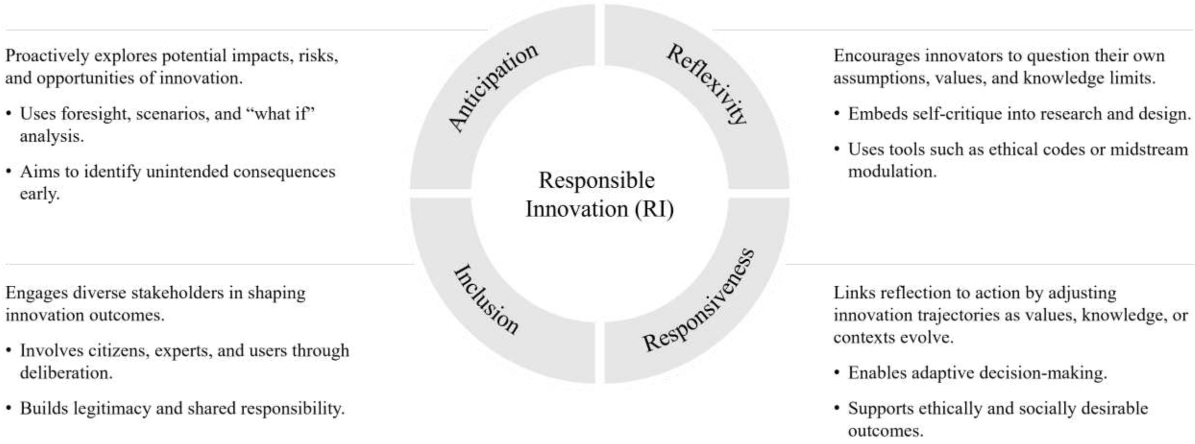
(III) BMI as an Organizational Change Process. A third perspective treats BMI as a process that unfolds over time and captures how firms enact and sustain BM change. External triggers include megatrends such as digitalization and sustainability as well as competitive disruption (Aagaard, 2024). Internally, a central driver is dynamic capability, the capacity to integrate, build, and reconfigure competencies (Aagaard, 2024; Foss and Saebi, 2017). Repeated BMI is itself often framed as such a capability (Zott et al., 2024). Frameworks commonly describe an iterative BMI cycle that spans initiation, ideation, integration, and implementation (Foss and Saebi, 2017). Building BMI capability is often explained as progressing from awareness to framing the design problem (goals, direction, constraints) to iterative design work (Zott et al., 2024). The process requires explicit top-management support (Foss and Saebi, 2018; Zott et al., 2024) and relies on experimentation, organizational learning, and low-cost prototyping to generate experiential knowledge (Aagaard, 2024; Zott et al., 2024). The effectiveness of BMI is moderated by organizational factors such as culture and structure (Foss and Saebi, 2017; Santa-Maria et al., 2021). Successful change depends on managing organizational ambidexterity and overcoming inertia (Santa-Maria et al., 2021). Firm characteristics such as size, age, industry, and geography may also play a role, although empirical findings are mixed on this (Santa-Maria et al., 2021). Finally, BMI is associated with a set of effects, including improved economic performance, enhanced competitiveness, increased strategic flexibility, and the creation of societal value, including environmental and social performance (Foss and Saebi, 2017; Geissdoerfer et al., 2017).

Recent research shows a stable positive relationship between novelty-centered BM design and firm performance, particularly in entrepreneurial contexts and across different environments (Zott and Amit, 2007). This process view is especially useful for studying AI-enabled transformation, as it foregrounds how technological opportunities are translated into sustained value through deliberate BM redesign rather than through technology adoption alone (Aagaard and Tucci, 2024; Jorzik et al., 2024b).

2.2 Responsible Innovation

Building on BMI's structural logic, this section consolidates RI as a framework for responsible value creation. RI integrates ethical, social, and environmental considerations directly into innovation processes (Hope and Moehler, 2015; Voegtlin and Scherer, 2017). In doing so, it shifts governance away from purely reactive risk management toward actively shaping innovation outcomes that are considered socially desirable (Owen et al., 2013). RI is often described as a collective commitment to responsible stewardship in science and innovation (Owen et al., 2013; Stilgoe et al., 2013), combining the dual objectives of preventing harm and actively contributing to sustainable development (Voegtlin and Scherer, 2017). From a policy angle, the European Commission frames RI as a transparent, interactive process in which innovators and societal actors jointly co-shape outcomes that are ethically acceptable, sustainable, and socially desirable (Hope and Moehler, 2015; Stilgoe et al., 2013).

A central challenge of RI lies in translating abstract ethical principles into concrete innovation practices and governance arrangements (Papagiannidis et al., 2025). Instead of viewing responsibility as mere duty, RI requires the continuous integration of ethical and social reflections throughout the entire innovation life cycle, with the explicit goal of achieving results that are not only acceptable but also socially desirable (Hope and Moehler, 2015). Its philosophical basis is a future-oriented commitment to care and responsible action, which is operationalized through four interdependent dimensions and forms the core process logic of RI: anticipation, reflexivity, inclusion, and responsiveness (Owen et al., 2013; Stilgoe et al., 2013), as further explained in Figure 2.



Author's own illustration based on (Owen et al., 2013; Stilgoe et al., 2013).

Figure 2. Dimensions of Responsible Innovation

RI also reflects a shift beyond traditional corporate social responsibility (CSR). While CSR has often focused on retrospective accountability and mitigating negative externalities, RI shifts responsibility forward to the development and management of new technologies (Owen et al., 2013; Stilgoe et al., 2013). In doing so, it does not replace CSR, but implements its normative obligations earlier in the innovation process and links corporate values with concrete technological and organizational design decisions (Hope and Moehler, 2015).

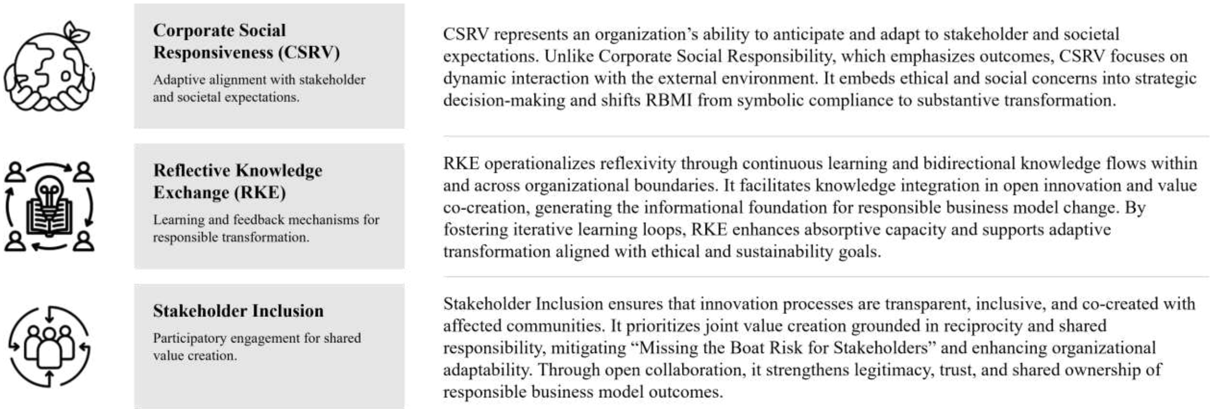
At the same time, RI has been criticized for its technology-centric focus, which can limit its transformative potential by maintaining the fundamental assumption that companies primarily exist to generate economic value through profit (Hope and Moehler, 2015). This critique highlights the need to extend RI beyond technology-oriented management to include integration at the corporate level. Recent work addresses this extension through RBMI, which locates responsibility at the intersection of profit orientation and social value creation (Hope, 2018; Hope and Moehler, 2015; Magni et al., 2024). The next section explains this logic.

2.3 Responsible Business Model Innovation

Conventional BMI models often prove to be an inadequate instrument for achieving responsible goals when they focus one-sidedly on profit maximization and neglect the socio-ecological transformation required by many of today's major challenges (Zott et al., 2024). RBMI addresses this limitation by integrating ethical corporate governance and sustainability into the core logic of its BM (Hope and Moehler, 2015). In this view, RI provides the normative dimensions that can enrich and redirect the BMI process (Owen et al., 2013; Stilgoe et al., 2013). The merging of RI and BMI thus establishes a systemic mechanism in which the dimensions of RI trigger changes in the BM architecture that support responsible outcomes (Magni et al., 2024).

2.3.1 Conceptual Foundations of Responsible Business Model Innovation

RBMI is defined as an extension of the BMI process that integrates ethical values and sustainability into the strategic core of a company while ensuring accountability and responsiveness to stakeholders (Magni et al., 2024). It is founded on the three pillars of corporate social responsiveness (CSRV), reflective knowledge exchange (RKE), and stakeholder inclusion, which are explained in more depth in Figure 3.



Author's own illustration based on (Magni et al., 2024).

Figure 3. Core Mechanisms of Responsible Business Model Innovation

The shift from BMI to RBMI occurs when RI's four dimensions trigger structural changes in BM architecture through the three RBMI mechanisms (Magni et al., 2024), as summarized in Table 1.

RI Dimension	Executed by RBMI Mechanism	Comparison to "Traditional" BMI Logic	Changes in BM Architecture
Anticipation	CSRV Provides the capacity to manage social and ethical challenges by analyzing unintended outcomes before they manifest.	Traditional logic uses risk assessment primarily to protect financial assets and ensure economic viability. RBMI logic moves from "responsibility as liability" toward "forward-looking care" for the future.	Introduces Negative and Positive Impact cases. Shifts Value Capture to account for long-term "right impacts" rather than just short-term profit.
Reflexivity	RKE Fosters a circular knowledge process to scrutinize the firm's own activities and underlying assumptions.	Traditional logic prioritizes internal design efficiency, centralization, and competitive edge. RBMI logic challenges assumptions of "scientific amorality" by blurring role responsibilities with wider moral obligations.	Reconfigures Mission, Vision, and Values to place purpose at the core of the BM. Alters Governance to include equity, diversity, and transparent decision-making.
Inclusion	Stakeholder Inclusion Shifting from a transactional approach (self-interest) to a relational approach (mutual respected interests).	Traditional logic focuses on maximizing value for paying customer segments to ensure profitability. RBMI logic views the firm as embedded in an "ecology" where value is co-created with non-paying users and affected parties.	Expands Customer Segments to include Users and Beneficiaries (e.g., marginalized groups or protected species). Redefines the Value Proposition toward solving social/environmental problems.
Responsiveness	CSRV and RKE Couples' reflection to action, allowing the organization to reconfigure resources in response to external socio-political pressures.	Traditional logic is reactive, adapting to technological shifts or market trends to sustain performance. RBMI logic requires "dynamic stewardship" to modulate the innovation trajectory based on collective deliberation.	Triggers Architectural changes in the activity system (the "What, How, Who, and Why" of transactions). Modulates Value Creation and Delivery pathways.

Author's synthesis based on (Aagaard, 2024; Magni et al., 2024; Owen et al., 2013; Pepin et al., 2024; Sjödin et al., 2023; Stilgoe et al., 2013; Våland and Heide, 2005; Voegtlin and Scherer, 2017; Zott et al., 2024; Zott and Amit, 2007).

Table 1. Integration of Responsible Innovation into Business Model Innovation

To understand this integration, one could view the RI dimensions as a compass that sets the direction for responsibility, while the RBMI mechanisms are the engine that actually reconfigures the gears of the BM architecture to move the company towards sustainable results (Magni et al., 2024; Stilgoe et al., 2013). A crucial constraint for RBMI is the need to maintain economic viability as a prerequisite while simultaneously striving for a positive net social effect (Hope, 2018).

2.3.2 Operationalization of Responsible Business Model Innovation

RBMI defines responsibility at the level of mechanisms and innovation processes, but ultimately it must be reflected in concrete BM design decisions (Magni et al., 2024). This design-level operationalization is captured by the Responsible Business Model Canvas (RBMC), which builds upon the traditional BMC and expands this framework to a total of fourteen components by introducing five additional components, as shown in Appendix B - Responsible Business Model Canvas (Pepin et al., 2024). These additions anchor responsibility directly in BM design by translating RI dimensions and RBMI mechanisms into tangible design elements (Pepin et al., 2024).

The process by which the five additional components of the RBMC operationalize the normative dimensions of RI through the core mechanisms of RBMI is summarized in Table 2.

RBMC Category	RI Dimension(s)	RBMI Mechanism(s)
Positive Impact	Anticipation; Responsiveness	CSRV
Negative Impact	Anticipation; Responsiveness	CSRV
Users and Beneficiaries	Inclusion; Reflexivity	Stakeholder Inclusion
Mission, Vision, and Values	Reflexivity; Anticipation	CSRV
Governance	Responsiveness; Inclusion	CSRV; Stakeholder Inclusion

Author's own compilation.

Table 2. Integrating Responsible Innovation, RBMI, and Business Model Canvas

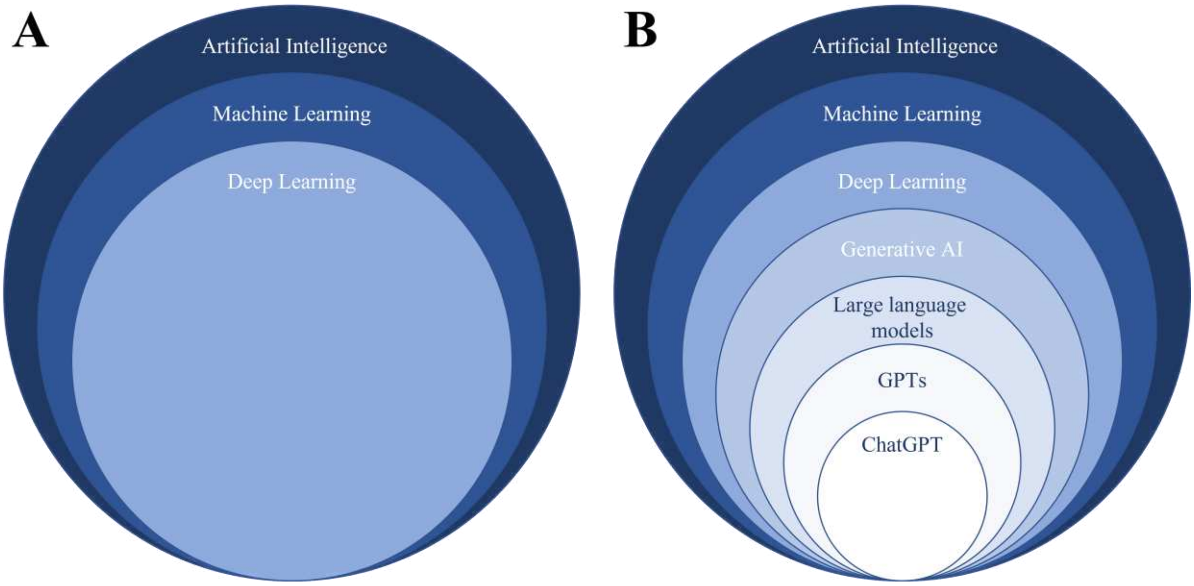
Notably, the RKE mechanism does not appear as a separate row in the table. This is because it functions as a transversal learning mechanism across all RBMC components and not as a discrete design element, which explains why it cannot be assigned to a single RBMC building block (Magni et al., 2024). Taken together, RBMI and the RBMC provide a coherent multi-level approach for embedding responsibility into BMs and BMI (Magni et al., 2024; Pepin et al., 2024). RI provides the normative orientation, RBMI translates this orientation into organizational mechanisms, and RBMC operationalizes responsibility at the business model design level (Magni et al., 2024; Owen et al., 2013; Pepin et al., 2024; Stilgoe et al., 2013). Therefore, RBMI offers a robust analytical perspective for examining how organizations can leverage new technologies like AI in a way that is not only economically viable but also ethically sound and socially legitimate (Kumar et al., 2023).

2.4 Artificial Intelligence and Business Model Innovation

AI is widely viewed as a transformative technology and a catalyst for BMI (Jorzik et al., 2024a, 2024b). In many contexts, AI-powered BMI is changing the way companies think about value creation and value realization, as data-driven predictions and personalization can transform both the offering and its delivery (Aagaard and Tucci, 2024). As BMI is defined as planned, novel, and non-trivial changes to the architecture of an activity system, it is catalyzed by AI as a transformative general-purpose technology that makes new activity configurations technically feasible and economically attractive (Åström et al., 2022; Jorzik et al., 2024b). In other words, AI often acts as a link between technical potential and realized business value, enabling companies to move beyond the traditional supply side through advanced predictive capabilities and finely tuned personalization (Aagaard and Tucci, 2024).

2.4.1 Foundations of Artificial Intelligence

To clarify the conceptual framework of AI used in this study, the following section provides an overview of the defining characteristics of current AI technologies. AI is defined as the ability of a system to interpret external data, learn from it, and apply this knowledge to achieve defined goals through adaptive behavior (Jorzik et al., 2024a). In practice, this adaptability can produce outputs such as predictions, recommendations, or synthetic content (Loaiza-Bonilla et al., 2025). AI is further classified by intelligence level and functional scope (Ferdelman et al., 2025; Toniolo et al., 2020). Artificial general intelligence refers to systems that do not yet exist but could compete with human levels of cross-domain thinking (Ferdelman et al., 2025), whereas artificial narrow intelligence encompasses all current applications optimized for specific tasks such as speech recognition, image analysis, and creditworthiness assessment (Sheikh et al., 2023; Toniolo et al., 2020). The evolution and hierarchy of this technology are shown in Figure 4.



(Loaiza-Bonilla et al., 2025).

Figure 4. Evolution and Hierarchy of Artificial Intelligence Technologies

The technological development of AI is typically described as a hierarchically nested structure. Machine learning (ML) represents a data-driven subfield of AI, while deep learning (DL) is a further specialization that uses multi-layered neural networks to learn complex representations, as shown in Figure 4-A (Loaiza-Bonilla et al., 2025). According to Figure 4-B, generative AI has evolved, building upon DL, including large language models (LLMs) such as generative pre-trained transformers (GPTs). Systems like ChatGPT illustrate this development at the application level as interactive tools for adaptive dialogues (Loaiza-Bonilla et al., 2025). The following section explains how this AI technology catalyzes BMI.

2.4.2 Artificial Intelligence in the Context of Business Model Innovation

Current literature distinguishes four perspectives on AI-driven BMI: technology implications, reconfiguration, focused BMI, and transformative BMI (Jorzik et al., 2024b). From these perspectives, organizations differ in how central AI becomes to the value creation logic, ranging from incremental process improvements to more radical configurations where AI forms the basis of the business model (Jorzik et al., 2024). In industrial contexts, firms often leverage perceptive, predictive, and prescriptive capabilities to develop BMs based on augmentation and automation (Sjödin et al., 2023). These models can promote a circular economy by optimizing resource use, extending product lifespan, and dematerializing consumption (Sjödin et al., 2023).

However, these advantages do not materialize automatically. Instead, previous research emphasizes the need for specialized dynamic capabilities, including value discovery, value realization, and value optimization, as organizations manage data pipelines and adapt to broader ecosystems (Sjödin et al., 2023). Furthermore, commercialization depends on linking these innovations with robust value creation mechanisms such as results-oriented contracts or licensing models (Åström et al., 2022). At the same time, inherent "black box" risks, where a lack of transparency in AI decisions limits understanding and accountability, and regulatory uncertainties need to be addressed (Åström et al., 2022). Ultimately, AI-powered BMI is not merely a technological adaptation but an ongoing organizational restructuring aimed at achieving sustainable competitive advantages in an increasingly data-driven global economy (Åström et al., 2022; Jorzik et al., 2024b).

2.4.3 Principles of Responsible Artificial Intelligence

In addition to conceptualizing responsibility within BMI and its operationalization through RBMI and the RBMC, this study also addresses responsibility as it applies to AI itself, given AI's role as a catalyst for transformation. Building on RI's normative foundations and emphasizing accountability (Fatima et al., 2021), fairness (Papagiannidis et al., 2025), and human-centric design (Ferdelman et al., 2025), RAI provides a foundation for translating responsible principles into data-driven and AI-enabled business practice (Papagiannidis et al., 2025). As AI systems become more complex and diffuse, risks to human welfare become harder to manage, including concerns related to fairness, privacy, and human autonomy (Häußermann and Lütge, 2022; Zimmer et al., 2022). RAI has therefore emerged as a framework for designing and deploying AI systems in ways that are ethical, safe, and trustworthy (Papagiannidis et al., 2025; Zimmer et al., 2022).

A widely accepted definition describes RAI systems as socio-technical systems in which AI agents and social entities jointly interpret data and adapt dynamically, and in which responsibility is assessed based on deontological and consequentialist criteria (Zimmer et al., 2022). In the literature, RAI is often discussed under terms such as "ethical AI", "trustworthy AI" or "principled AI", which refer to high standards for fairness, accountability, and data protection (Aagaard and Tucci, 2024; Kumar et al., 2023; Zimmer et al., 2022). In 2019, the European Commission's High-Level Expert Group on AI suggested a set of requirements for trustworthy AI, summarized in Table 3 (High-Level Expert Group on AI, 2019).

Requirement	Core Principle	Illustrative Focus
Human Agency and Oversight	Preserving meaningful human control, understanding, and intervention in AI supported decision making.	Ensuring that humans remain “in the loop”, empowered to understand, supervise, and intervene in AI supported decision processes.
Technical Robustness and Safety	Ensuring AI systems operate reliably, securely, and safely across expected and unexpected conditions.	Safeguarding the reliable, secure, and resilient functioning of AI systems under both expected and adverse conditions.
Privacy and Data Governance	Safeguarding personal data through responsible collection, processing, access control, and governance practices.	Protecting personal data and ensuring responsible data practices across collection, processing, access, and storage.
Transparency	Enabling traceability, explainability, and intelligible communication of AI system functioning and outcomes.	Making AI systems and their outcomes traceable, explainable, and communicable to relevant stakeholders.
Diversity, Non-discrimination, and Fairness	Preventing biased outcomes while ensuring equitable treatment across individuals and social groups.	Preventing biased or exclusionary outcomes while promoting equitable treatment across different individuals and groups.
Societal and Environmental Well-being	Aligning AI development with societal values, democratic principles, and environmental sustainability.	Aligning AI development and use with broader societal values, democratic principles, and environmental sustainability.
Accountability	Establishing clear responsibility, auditability, and effective mechanisms for oversight and redress.	Ensuring clear responsibility, auditability, and effective mechanisms for oversight, remediation, and redress.

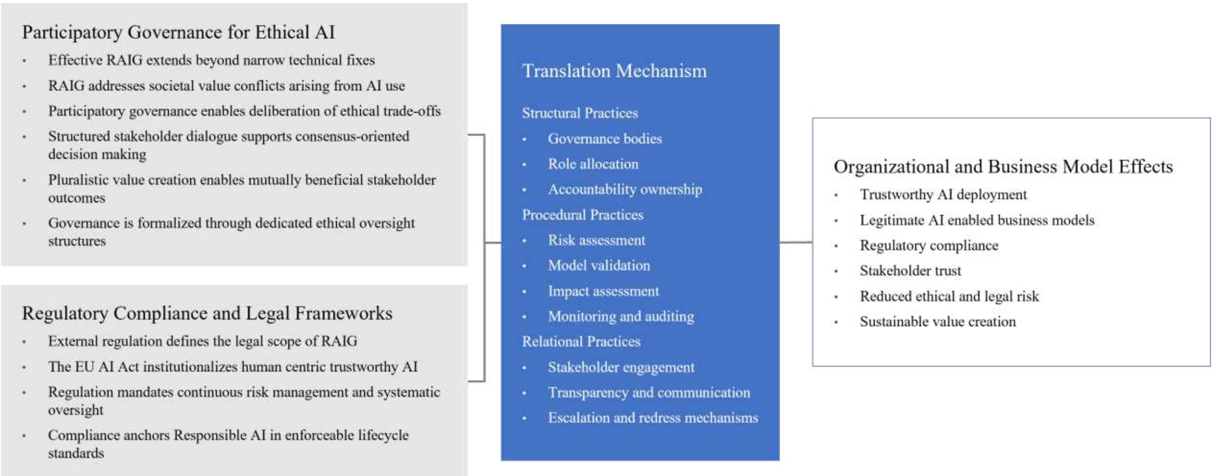
Author’s adaptation based on (High-Level Expert Group on AI, 2019).

Table 3. Key Requirements for Trustworthy Artificial Intelligence

It is important to understand that responsibility in the context of AI cannot be attributed solely to the algorithms. Rather, it arises from the interplay of technical design decisions with organizational processes and broader societal practices (Zimmer et al., 2022). At the operational level, these concerns are institutionalized through responsible AI governance (RAIG), which refers to the structural, procedural, and relational practices that organizations use to manage responsibility across the entire AI lifecycle (Papagiannidis et al., 2025). In this field of research, RAI is also conceived as a third-order construct based on three pillars: technical capabilities, ethical concerns, and risk reduction (Kumar et al., 2023).

2.4.4 Integrating Responsible Artificial Intelligence into Business Models

A core difficulty in RAI lies in translating abstract ethical principles into practical implementation approaches, which is attempted through the establishment of RAIG (Papagiannidis et al., 2025). In the literature, RAIG is shaped by two interconnected forces. On the one hand, by ethical considerations that emphasize participatory governance and pluralistic value creation. On the other hand, by regulations that formalize accountability through binding compliance mechanisms (see Figure 5).



Author’s synthesis based on (Balcioğlu et al., 2025; Butt, 2024; European Parliament and Council, 2024; Ferdelman et al., 2025; Häußermann and Lütge, 2022; Lüdeke-Freund et al., 2024; Papagiannidis et al., 2025; Zimmer et al., 2022).

Figure 5. Translating Ethical and Regulatory Logics into Responsible AI Governance

Together, these forces translate principles into governance routines that can embed responsibility in the design of business models and innovations. However, empirical studies reveal a persistent maturity gap: While the strategic maturity of RAI (e.g., top-level support and risk identification) has improved, operational RAI maturity (e.g., system-wide safeguards to reduce biases or measure environmental impacts) often lags behind (Brynjolfsson and McAfee, 2017; Maslej et al., 2025). This gap suggests that RAIG must function as a continuous process of capturing, adapting, and integrating new requirements as societal expectations and legal obligations evolve (Papagiannidis et al., 2025).

Commercializing RAI involves ongoing tension between profitability, efficiency, and societal values such as fairness and privacy (Zimmer et al., 2022). Regulation can restrict the space for innovation and, in some cases, create paradoxes instead of clear considerations (Holst et al., 2024). However, applying the RAI principles can increase both performance and trust by improving data quality and stakeholder confidence (Zimmer et al., 2022). Zimmer et al. (2022) describe two approaches: a “corner path” in which organizations prioritize economic viability before integrating responsibility, and a “direct path” in which responsibility is anchored as an equal design goal from the outset. Since RAI is socio-technical, accountability depends on both technical and social responsibilities. Establishing criteria upfront and conducting subsequent audits together shape credible accountability (Zimmer et al., 2022). Overall, RAI provides a procedural and relational infrastructure for transparency, fairness, and compliance across the entire AI lifecycle, thus directly linking ethical governance with innovation in the business model.

2.5 Drivers of Artificial Intelligence Enabled Business Model Innovation

Building on the integrative logic of RBMI, this section describes external and internal prerequisites that influence both AI adoption and the effectiveness of mechanisms for RI. The implementation of RBMI through AI depends on how external pressures align with internal capabilities (Foss and Saebi, 2018; Jorzik et al., 2024b). External framework conditions both limit and accelerate AI-driven transformation in regulatory, societal, and competitive areas (Black et al., 2024). Regulation plays a particularly important role, as political initiatives, including the EU AI Act, increasingly require organizations to demonstrate safety and accountability through risk management documentation and continuous oversight (Balcioğlu et al., 2025; Butt, 2024). This evolving landscape increases the need for formal RAIG structures and organizational agility in maintaining governance (Papagiannidis et al., 2025).

Societal and sustainability challenges further intensify these pressures. Climate change, inequality, and evolving norms can raise expectations for sustainability-oriented innovations and reinforce demands for transparency and accountability in the use of AI (Hope and Moehler, 2015). These expectations can also institutionalize stakeholder engagement through adaptive governance frameworks such as ISO 26000, an international guide for CSR (Herrmann, 2023). Market and ecosystem dynamics underscore the need for continuous adaptation of business models (Jorzik et al., 2024b), while open innovation often requires collaboration with various stakeholders to gain access to the expertise and infrastructure needed to scale AI solutions (Füller et al., 2022). At the ecosystem level, initiatives such as the European Partnership for AI, Data and Robotics aim to promote dissemination and coordination (European Commission, 2021).

Internal drivers determine whether organizations can translate external pressure into capability and advantage (Black et al., 2024; Jorzik et al., 2024b). AI-enabled transformation typically requires data readiness, financial resources, and digital infrastructure that can support integration (Black et al., 2024). Furthermore, the literature suggests that technical readiness alone is not sufficient, but that leadership, an innovation-oriented culture, and AI-sensitive risk tolerance shape how organizations deal with uncertainty and resistance, especially under changing regulatory frameworks (Black et al., 2024; Jorzik et al., 2024b). At the process level, effective implementation of RAI depends on structured practices such as strategic reviews and decisive leadership action, coupled with organizational ambidexterity that maintains ongoing operations while enabling transformation (Black et al., 2024). Overall, AI-driven RBMI emerges from the interplay of external constraints and internal factors (Black et al., 2024), mediated by strategic decision-making and organizational maturity (Åström et al., 2022; Jorzik et al., 2024b).

2.6 Artificial Intelligence in Healthcare

To ground the aforementioned literature within a field where questions of responsibility play a crucial role, this section positions healthcare as a particularly insightful environment for examining AI-driven innovations. AI is increasingly being used to support diagnosis, treatment, and patient management through ML and related cognitive technologies (Brynjolfsson and McAfee, 2017; Zeb et al., 2024). The benefits of AI typically lie in increased efficiency, improved precision, faster insights, reduced treatment variability, and the potential for personalized and precision medicine (Koski and Murphy, 2021). Applications range from diagnostics and therapy optimization to accelerating research and improving care management. However, alongside these benefits arise significant ethical, legal, and technical challenges (Bouderhem, 2024). RAI is therefore central for mitigating risks such as algorithmic bias, data breaches, and privacy violations, while also supporting equitable access to AI-enabled benefits (Kumar et al., 2023).

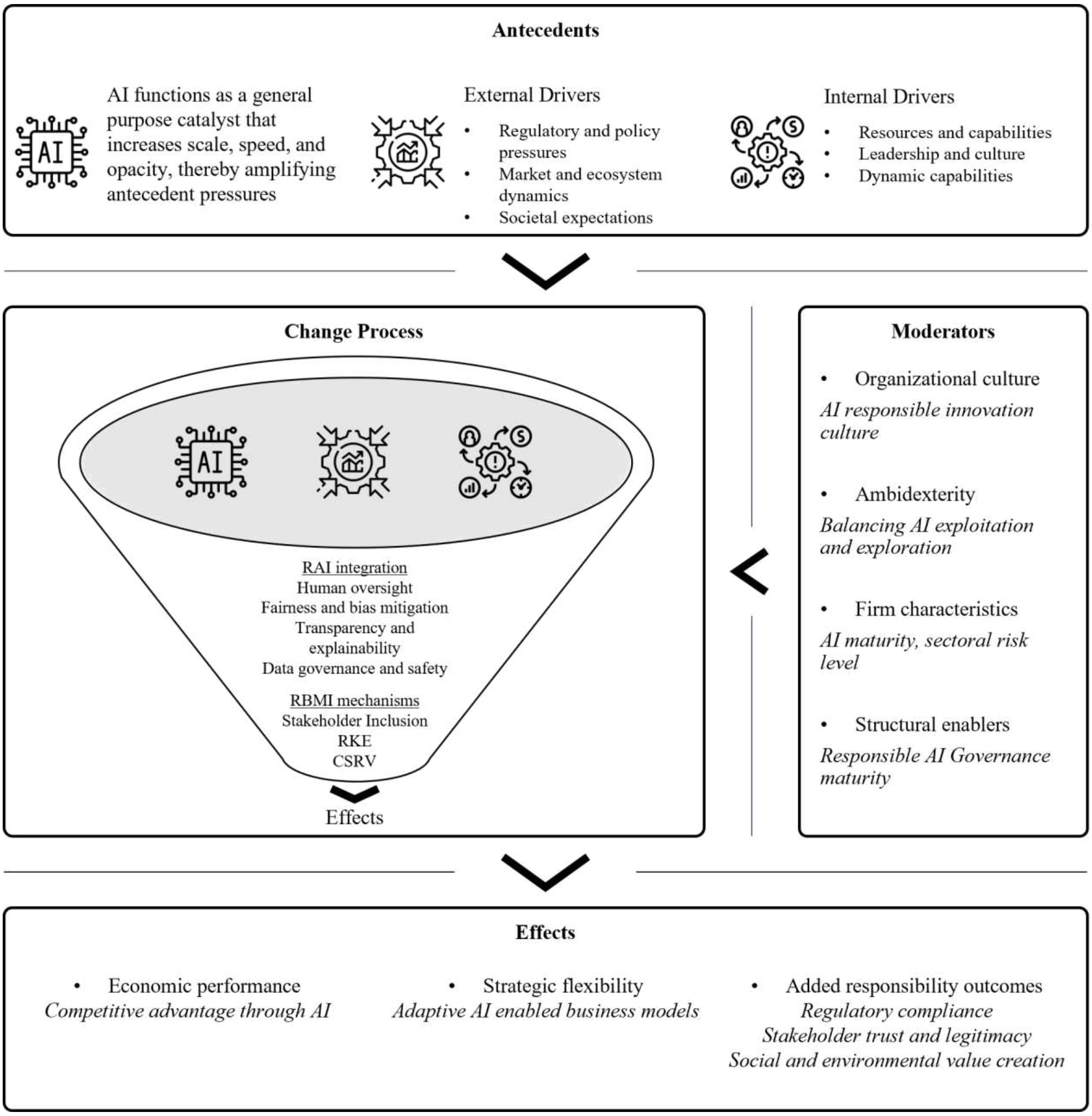
A robust application of RAI can strengthen the trust of physicians and patients and support safer integration into clinical workflows (Saenz et al., 2024). The European Union (EU) offers a particularly relevant geographical context for the further research of this thesis, as on the one hand its regulatory approach is comparatively prescriptive and user-centric, including the GDPR, the Data Protection Act, and the AI Act (Bouderhem, 2024; Van Genderen et al., 2025), and on the other hand it is characterized by its single market (Ulnicane, 2022). In this context, many medical AI systems are classified as "high-risk systems" and are subject to stringent transparency and accountability requirements under the AI Act, making the EU a comprehensive and analytically rich context for investigating how the governance of clinical AI can be designed to be effective, equitable, and trustworthy (Bouderhem, 2024; Van Genderen et al., 2025). Therefore, anchoring responsibility in healthcare innovation models is a practical way to reconcile technological opportunities with professional duty, and it motivates the methodological approach developed in Chapter 3.

2.7 Summary and Transition to Methodology

The literature suggests that RBMI represents a meaningful extension of BMI in contexts where AI-driven transformations must be aligned with ethical and societal expectations. While traditional BMI often prioritizes efficiency and competitive advantage, RBMI shifts the focus to embedding responsibility in the core value logic of the business model. This perspective not only supports the redesign of value creation and realization through AI but also the anticipation and mitigation of negative impacts and, where possible, the achievement of positive net outcomes through responsible corporate governance, operationalized using RBMI mechanisms (Magni et al., 2024; Owen et al., 2013; Stilgoe et al., 2013).

From this perspective, responsibility is not an external constraint added after implementation. It functions as a constitutive design principle that shapes the transformation of business models from the outset (Lüdeke-Freund et al., 2024; Owen et al., 2013). Because AI systems are sociotechnical, responsibility does not reside solely in their algorithms. It arises from the interplay of technical design decisions with organizational and societal practices, making governance a central component of AI-driven business model innovation (Papagiannidis et al., 2025; Zimmer et al., 2022). Table 2 summarized how RI dimensions and RBMI mechanisms are translated into RBMC design elements.

To investigate this responsible form of AI-enabled BMI this dissertation analyzes how RBMI is implemented when AI gets adopted and which mechanisms influence its implementation. Figure 6 serves as a guide for this investigation. It builds on the BMI as organizational change process literature-based synthesis (Figure 1) by Santa-Maria et al. (2021). Building on this framework, the next chapter examines the organizational drivers and constraints that shape responsible AI governance, as well as the implementation of accountability at the BM design level. The methodology is tailored to the European healthcare context, where many AI applications are associated with high risks and prescriptive regulations reinforce the requirements for accountability and transparency.



Author's own illustration

Figure 6. AI-Catalyzed Responsible Business Model Innovation Framework

3 Methodology

This study used a qualitative research design to examine AI-enabled RBMI in healthcare as a socially embedded and continuously evolving practice. The qualitative approach proved particularly well-suited to capturing contextual nuances, organizational complexity, and the processes of meaning-making through which AI adoption and responsibility are negotiated in practice (Creswell and Poth, 2018; Gioia et al., 2013).

To focus the investigation, the study employed a single instrumental case study design (Creswell and Poth, 2018). The aim was to explore the research question using a bounded case to illuminate this phenomenon (Creswell and Poth, 2018; Stake, 1995). This case study focuses on the introduction of AI in European healthcare. Within this single case, 15 interviews were conducted. These interviews were treated as embedded sources of evidence rather than as separate cases, enabling a deeper understanding of the bounded case as a whole (Creswell and Poth, 2018). The entire research process followed established qualitative guidelines, which are summarized in Figure 7 (Darlington & Scott, 2020).

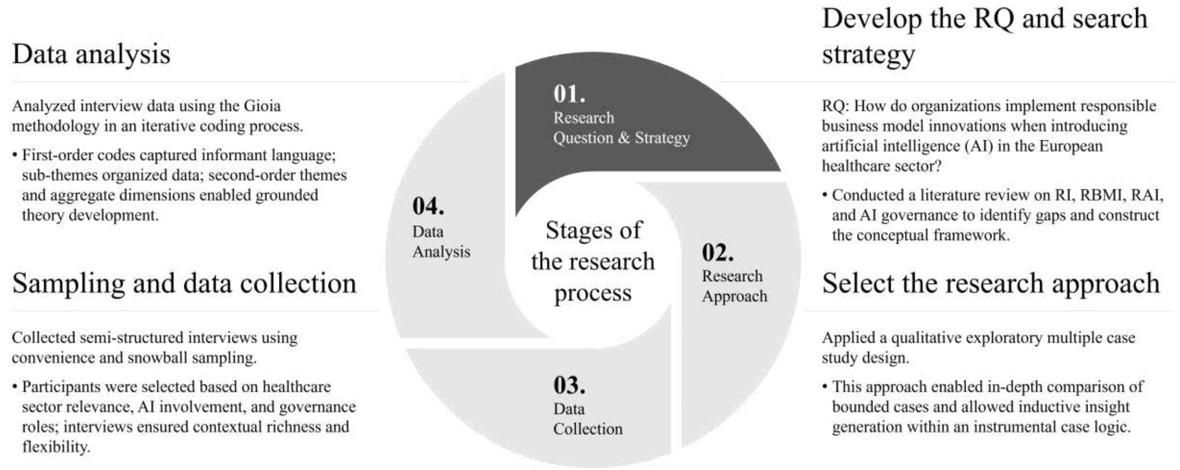


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Figure 7. Research Design, Methods, and Process Overview

Following the development of the research question and the literature review, a sampling frame was specified. Interviewees served as embedded units of analysis within the single bounded case, allowing the study to examine the broader issue through diverse roles and perspectives (Creswell and Poth, 2018). The study followed a theory-informed yet inductive orientation (Creswell and Poth, 2018; Williams and Moser, 2019). The conceptual framework developed in Chapter 2 served as the basis for case selection and enhanced the analytical approach while still leaving room for new insights and concept development to emerge from the interview data (Gioia et al., 2013; Williams and Moser, 2019). In line with the Gioia approach, the goal was to develop and refine the conceptual model (Creswell and Poth, 2018) rather than test fixed causal relationships, which is consistent with qualitative traditions that emphasize flexible design and emergent theory building (Gioia et al., 2013; Williams and Moser, 2019).

Sampling combined criterion, convenience, and snowball logic, reflecting practical constraints on time and access (Suri, 2011). Participants were selected using criterion sampling (Palinkas et al., 2015), based on four requirements: (1) they were professionals in healthcare or adjacent sectors, (2) involved in applying AI technology to healthcare, (3) held roles pertinent to innovation, governance, or clinical practice, and (4) conducted their activities within the

European context. After identifying initial informants, further participants were recruited through recommendations in order to broaden the range of relevant perspectives within the case (Creswell and Poth, 2018). Data collection was primarily based on semi-structured interviews. The interview guide, which can be found in Appendix C - Semi-Structured Interview Guide, was based on the conceptual dimensions developed in the literature review. The interviews lasted around 30 to 45 minutes and were conducted either in person or via video conference. In one instance, an interviewee answered the guiding questions in writing. All interviews were recorded with the participants' consent and transcribed verbatim. For better comprehensibility, Appendix D - Interview Summaries contains an AI-supported summary of each interview (Creswell and Poth, 2018), ensuring a consistent tone and analytical depth across cases while full researcher oversight and responsibility for all analytical decisions were maintained.

The data analysis followed the Gioia methodology, which provides a structure for inductive qualitative research and theory development (Gioia et al., 2013). All interview transcripts were treated as one pooled dataset representing the single bounded case, consistent with single bounded case study logic that seeks to understand a puzzling phenomenon by studying a particular case in depth (Creswell and Poth, 2018; Stake, 1995). The analysis was conducted in four iterative steps. First, first-order concepts were generated using informant-centered coding, as documented in Appendix E - Gioia First-Order Concepts. To support this coding, AI was used to assist in the systematic review of interview transcripts and the identification of potentially relevant text passages, which were then manually coded into concepts by the researcher. The participant's language was retained to capture their experiences and interpretations. This phase yielded 648 concepts, reflecting the breadth of the dataset. These concepts were then broken down into 53 conceptually similar sub-themes. This served as an intermediate step before abstraction. Third, the sub-themes were examined for relationships and grouped into 15 theory-centered second-order themes that captured overarching patterns in the case study. Fourth, the second-order themes were synthesized into four aggregated dimensions. These represent the highest level of abstraction and form the analytical framework for the results presented in Chapter 4 (Magnani and Gioia, 2023). This coding process enabled clear transparency and traceability from the raw data to the higher-level insights (Magnani and Gioia, 2023).

4 Results

Table 4 presents the results thematically based on the four aggregated dimensions that emerged from the analysis. The results are structured as follows: "Augmentation" describes how organizations use AI in specific healthcare applications to enhance clinical, administrative, and cognitive capabilities. “Embedding” examines the organizational frameworks and adoption dynamics that integrate these applications into everyday workflows. “Legitimation” focuses on governance, validation, and oversight practices that ensure responsible, trustworthy, and compliant AI use. “Reconfiguration” summarizes the long-term impact of AI adoption on organizational capabilities, professional roles, and care models. Together, these dimensions provide an integrated view of how RBMI is implemented in AI-enabled healthcare settings.

Exemplary Concepts	Sub-Themes	Themes	Dimension
AI as radiology second reader / second opinion Machine vision converts images to diagnoses AI superior when trained on millions of images	AI-supported diagnostic imaging and radiology AI-enabled cardiology and specialized diagnostic support Robotic and embodied AI in clinical and surgical settings AI-assisted support for complex and rare clinical cases	Applying AI in Diagnostic Imaging and Complex Cases	Augmentation
AI clinic note generation as major impact Use of LLMs and speech-to-text in documentation Global rollout of AI clinic note tools	AI-driven clinical documentation automation AI-enabled administrative and operational workflow support Documentation quality improvement and administrative burden reduction Automation of repetitive clinical and administrative tasks	Automating Clinical Documentation and Administrative	
AI used to refresh knowledge and update evidence AI used for idea generation and scoping literature AI supports literature retrieval for rare findings	AI-based information retrieval and evidence synthesis Language and communication support for migrant healthcare professionals AI-supported workload management and capacity optimization	Retrieving Medical Information and Managing	
Time scarcity as central barrier Limited time and regulatory capacity at employers Strong workload prevents deeper AI engagement	Temporal constraints in clinical AI adoption and learning Workforce shortages as drivers of AI-enabled care continuity Clinician skepticism and resistance toward AI technologies	Facing Time Scarcity and Workforce	Embedding
AI solutions perceived as too expensive Lack of reimbursement for AI limits implementation Budget myopia blocks proactive AI investment	Economic and reimbursement barriers to AI adoption Cost-efficiency–driven AI business model logics Infrastructure and deployment constraints in healthcare AI	Encountering Economic Pressures and Infrastructure	
Physicians self-initiating AI use Bottom-up AI adoption without strategy Autodidactic, bottom-up AI adoption by residents	Bottom-up clinician-led AI experimentation and peer diffusion Top-down and bottom-up implementation tensions in AI integration Shadow AI use outside formal organizational governance	Engaging in Grassroots Experimentation	
AI as "today's fancy word" and hype driver Fear of missing out (FOMO) Echo chamber of success stories	AI hype cycles and fear-of-missing-out adoption dynamics Problem-driven versus tool-driven AI adoption approaches Iterative piloting and experimental learning in AI implementation	Navigating Hype-Driven Adoption and Pilot	
AI can misclassify rare patterns (button as tumor) AI cannot distinguish clinically irrelevant warnings AI requires narrow, domain-specific training	AI performance limitations and hallucination risks Error reduction and safety enhancement through AI support Clinical validation and continuous performance monitoring of AI systems	Addressing AI Errors and Demanding Clinical	Legitimation
No formal AI oversight structures or roles No lifecycle governance for AI systems AI use lacks organisational governance and documentation	Absence of formal AI governance and accountability structures Strategic AI governance bodies and oversight committees Operational AI governance processes and risk monitoring Risk-based classification of AI systems for governance purposes	Establishing AI Governance Structures and Risk Oversight	
Higher governance requirements Responsibility shapes model architecture Data use constrained by responsibility	Embedding ethical and responsibility principles into AI governance Trust-building mechanisms for AI acceptance in clinical practice Limited institutional capacity for ethical and societal AI reflection	Embedding Ethical Reflection and Building Trust	
Emphasis on EU-compliant data protection in startup Data protection seen as essential baseline Multi-regulatory environment (GDPR, HIPAA)	Data protection and privacy compliance as core AI governance focus Data security and misuse risks in healthcare AI Navigating international regulatory frameworks for medical AI Regulatory enforcement as a constraint on AI deployment Perceived regulatory rigidity within the European AI context	Complying with Data Privacy Regulations and Security Requirements	
Humans handle difficult decisions without AI No automated or AI-based final decisions AI viewed as supportive knowledge tool, not decision-maker	Human-in-the-loop oversight and retained clinical responsibility Primacy of physician expertise over algorithmic recommendations Opacity and black-box challenges in AI decision-making Preference for explainable and interpretable AI systems	Maintaining Human Oversight Amid Black-Box Opacity	
Co-creation and continuous competence development Need to train users on language and bias in AI interactions AI literacy as societal goal by 2030	AI literacy and capability development through training and education Skill and confidence gaps due to insufficient AI training Institutional gaps in formal AI education within medical curricula	Developing AI Literacy and Addressing	Reconfiguration
Interdisciplinary teams support AI Holistic 360° approach and admitting limits Building internal AI "community of practice"	Cross-functional collaboration in healthcare AI development Leadership support and experimentation-oriented organizational cultures Clinician–AI expert collaboration in model development and interpretation	Fostering Cross-Functional Collaboration and	
AI should augment, not replace, clinicians (10-year horizon) AI as supportive tool with human in the loop Unsure whether AI can replace physicians	Augmentation versus replacement tensions in clinical AI adoption Employment disruption and power concentration concerns AI-enabled role transformation and capacity-building futures Perceived inevitability of AI-driven healthcare transformation Patient engagement and transparency in AI-supported care	Confronting Job Displacement and Shifting Care Models	

Author’s own compilation.

Table 4. Aggregated Gioia Data Structure

To keep Table 4 concise, only three exemplary first-order concepts are presented for the first sub-theme of each theme. The complete data structure can be found in Appendix F - Full Gioia Coding Structure. Table 5 summarizes the interview sample and provides the profile of the interviewees who represent the single instrumental case underlying the analysis, including their role, health-related sector, and type of organization.

Interviewee No.	Interview Title	Role of Interviewee	Sector	Organization Type
1	AI in Daily Urology Practice	Urologist; early-career clinician and AI startup co-initiator	Hospital clinical care – urology; digital health innovation	Hospital & Startup
2	MedTech Expert on Responsible AI in Surgery	MedTech executive and consultant for surgical AI and devices	MedTech / medical devices; digital surgery	Industry & Consulting
3	AI Adoption Expert on Responsible Healthcare Innovation	CEO of digital health startup bridging clinics and AI	Digital health / AI clinical documentation	Startup
4	Cardiologist on AI-Enabled Diagnostics	Hospital cardiologist / angiologist in specialty training	Hospital clinical care – cardiology	Hospital
5	Neurology Clinician on AI in Everyday Practice	Hospital neurologist in acute and emergency care	Hospital clinical care – neurology	Hospital
6	Health-IT CEO on Responsible Clinical AI	CEO of hospital documentation and workflow software vendor	Health IT / hospital information systems	Health-IT Vendor
7	Frontline Educator's Perspective on AI in Nursing Education	Nurse educator and intensive/anaesthesia programme lead	Nursing education and clinical training	Hospital Education
8	Radiologist on AI in Everyday Imaging	Radiologist; former practice owner now employed	Diagnostic radiology / imaging	Outpatient Clinic / Practice
9	Physician-Executive on Responsible AI in Healthcare	Physician-entrepreneur; MedTech and digital health founder	Digital health; medical AI platforms	Startup
10	Clinical Caution and Emerging AI Utility in Specialist Cardiology	Outpatient cardiologist in internal medicine / cardiology	Outpatient specialist cardiology	Outpatient Clinic / Practice
11	Ethical Caution and Efficiency Constraints in AI for Cardiology	Cardiologist preparing new outpatient practice	Outpatient cardiology	Outpatient Clinic / Practice
12	Physician-Founder Leadership in Governing Responsible AI for Healthcare Innovation	Urologist; founder and executive lead of medical AI non-profit	Healthcare AI governance and enablement	Non-profit
13	AI and Data Engineering Leadership in Healthcare AI Adoption	AI and data engineering leader; generative AI and LLM expert	AI / data engineering with healthcare clients	Tech / Consulting
14	Data-Driven Digital Pathology Innovation and AI Startup Consulting in Healthcare	Pathologist and oncology PhD; digital pathology and AI consultant	Pathology / oncology; digital health and life sciences	Independent Consulting
15	Data Scientist Leader in Healthcare AI Innovation	Data scientist / engineer specialising in telemedicine and diagnostic AI	Healthcare AI; telemedicine and decision support	Startup / Telemedicine

Author's own compilation.

Table 5. Interview Sample Profile

4.1 Augmentation

The dimension of "Augmentation" describes how AI is already being used in clinical practice in three areas. First, AI supports diagnostics, particularly in radiology and cardiology, as well as in complex cases where physicians face uncertainty. Second, AI reduces administrative workload by automating documentation and routine text generation. Third, AI helps physicians manage the increasing flood of information by accelerating evidence searches, providing language support, and, in certain areas, enabling robotic assistance. These areas are described in detail in the following sections.

4.1.1 Applying AI in Diagnostic Imaging and Complex Cases

Interviewees described four main areas of application for AI in diagnostic imaging and complex cases: automation in radiology, specialized cardiology diagnostics, robotics, and support for complex cases. In radiology, AI is frequently used as a "second reader" working alongside clinical interpretation. It automates routine examinations and quantitative analyses such as staging and volumetry: “AI… in parallel… both say ‘tumor’ or not… you’ve had a second set of eyes.” (Interviewee 2). Several participants expect this to expand into a comprehensive automation of normal X-ray and ultrasound examinations, with AI-driven volumetry already mandated in certain screening regulations: “AI is required for lung cancer screening.” (Interviewee 8).

In specialized cardiology, AI supports the detection of subtle changes in the electrocardiogram (ECG), heart attack detection, and the recommendation of stent parameters: “The AI does this overwhelmingly well… better than our experienced senior consultants.” (Interviewee 4). These diagnostic procedures are based, among other things, on the integration of multimodal data: “Mammogram is… one context but… further test you require like blood tests or other tests.” (Interviewee 15). This would allow, for example, family history and clinical data to be integrated into models tailored to specific regional population groups.

In complex case support tasks, AI acts as an “idea generator” for rare diagnostic edge cases: “It’s like ideas or first insight… to get quickly to the relevant information.” (Interviewee 5). By using agentic AI to retrieve previous cases and research results, it serves as an evidence-based tool for harmonizing clinical decisions and supporting difficult differential diagnoses: “Same data is same but the decision is different… this kind of problem can be solved by AI.” (Interviewee 15). Finally, the subtopic of robotics and physical AI highlights highly precise surgical instruments and assistive technologies for communicating with intubated patients: “Robots like Da Vinci are already very good.” (Interviewee 11). Although concerns about uncertainties and human oversight still create a gap between research and clinical application, scanner-integrated “acceleration modules” are already improving the quality and speed of diagnostics: “Colleagues bought AI acceleration… it’s worth the money.” (Interviewee 8). Overall, these advances enable AI to act as a crucial pre-reader of the explosive growth of imaging data: “Millions of findings behind it… better than freehand ultrasound.” (Interviewee 10).

4.1.2 Automating Clinical Documentation and Administrative Tasks

The automation of documentation and administrative tasks aims to reduce bureaucratic hurdles in various use cases. Clinical documentation automation utilizes comprehensive language models and speech recognition to create structured notes, simplify medication dosing, and facilitate shared access to patient records: “Based on LLM and… speech to text conversion.” (Interviewee 15). This transition is essentially motivated by the improvement of documentation quality and the reduction of documentation effort, with manual paperwork being identified as the main obstacle to direct patient care: "I sit an extra hour with documentation instead of doing what I was trained for." (Interviewee 5). AI interventions in this area improve error traceability and drastically shorten research cycles, effectively freeing up clinicians for their core medical tasks: "Goal is to free trained professionals so they can really focus on medicine and people." (Interviewee 3).

At the same time, support for administrative workflows optimizes processes through semi-automated appointment scheduling and AI-assisted data retrieval, for example, for comprehensive medication histories: "We bought a program… Apenio… introduced by the hospital." (Interviewee 5). Finally, the automation of recurring tasks addresses the high workload in the regulatory area. By creating text-heavy dossiers and replacing manual data extraction: "If you shorten writing by two, three, four, five months, that's a lot of money." (Interviewee 6), AI serves as a tool for job substitution, enabling scarce skilled workers to move from routine data processing to higher-value strategic tasks: "Professionals are scarce… better to use them for thinking, not just writing documents." (Interviewee 6). Taken together, these advances are changing clinical time by delegating intensive bureaucratic work to machine systems.

4.1.3 Retrieving Medical Information and Managing Workloads

According to the findings, the increasing complexity of clinical data is being addressed through three different areas of AI application. Information retrieval and evidence synthesis utilize tools such as Open Evidence and ChatGPT as "clinical research assistants" to navigate the "overwhelming journal landscape" (Interviewee 4). These systems provide validated study summaries, support treatment decisions, and offer AI-assisted differential diagnoses that often surpass manual research: "It gave a perfect differential diagnosis." (Interviewee 8). This functionality serves as an important guideline shortcut and enables rapid knowledge updates and the retrieval of relevant literature.

This is complemented by AI language support, which represents an important access point for physicians with a migration background by reducing language barriers and facilitating the understanding of technical documentation: "This reduces language barriers and accelerates clinical and research tasks." (Interviewee 1). Ultimately, workload management focuses on system throughput, not just time savings. By acting as a "pre-reader" of large image datasets and structuring complex information for faster understanding, AI relieves the burden on clinicians, allowing them to dedicate themselves to more targeted specialized research and make more informed decisions: “Used to present complex issues in a clear and structured way, thus enabling faster comprehension.” (Interviewee 1). Overall, these advances enable clinicians to manage the “explosion of imaging data” and synthesize insights with unprecedented speed and clarity (Interviewee 8).

4.2 Embedding

The “Embedding” dimension reveals a tension between systemic barriers and catalysts for the adoption of new technologies. While time constraints and economic pressures, including inadequate reimbursement, hinder integration, the shortage of skilled personnel necessitates the adoption of AI. Implementation is characterized by conflicts between grassroots experimentation, often manifesting as “shadow AI”, and top-down directives. Consequently, organizations must navigate hype-driven cycles by employing problem-oriented strategies and iterative pilot studies to bridge the gap between technological potential and clinical workflow.

4.2.1 Facing Time Scarcity and Workforce Shortages

This section offers insights into the issue of facing time scarcity and workforce shortages and reveals a profound systemic paradox, namely that clinical pressure both hinders and necessitates the integration of AI. Time scarcity represents a major obstacle, as excessive workload prevents structured introduction, team reflection, and the ethical considerations essential for responsible implementation: “We are so tightly scheduled… there’s no time to deal with it additionally.” (Interviewee 5). These lacks of resources reduce motivation for peer exchange and limit professional development opportunities for existing staff: “Surgeons… don’t have time to exchange… it’s just for me… can’t write it down.” (Interviewee 2).

Paradoxically, the shortage of skilled workers is a major driver for AI, which is positioned as an unavoidable necessity to maintain the quality of care in the face of demographic crises and increasing patient severity: “Baby boomer… every year we’re losing people… AI is definitely going to become mandate.” (Interviewee 2). Staffing constraints and resource scarcity are forcing companies to use AI-supported “staff relief” instead of replacing workers: “It’s not about saving staff… we don’t have any to save.” (Interviewee 7). Furthermore, resistance from hospital staff and deficits in digital competence, especially among employees without digital training and conservative health authorities, lead to friction during the generational transitions in mindset: “Old physicians are going to retire with the old legacy system of thinking.” (Interviewee 9). These deficits in AI competence and skepticism towards AI tools suggest that while the shortage of skilled workers necessitates technological interventions, the prevailing time constraints significantly hinder the transition from theoretical potential to practical clinical application.

4.2.2 Encountering Economic Pressures and Infrastructure Constraints

The analysis further revealed that encountering economic pressures and infrastructure constraints examines the financial and technical hurdles to the adoption of AI. Economic hurdles include high implementation costs and a widespread lack of reimbursement for certain applications, such as AI-assisted mammography: “It’s of course a cost question.” (Interviewee 11). This is exacerbated by “budget myopia” and the resistance of patients and employers to financing instruments without clear financial benefit: “My budget today… gets spent this year… how can I spend… on stuff…with a horizon of 10 years time?” (Interviewee 2). Consequently, when adopting such tools, BMI often tends towards a “cheapest-solution bias”, prioritizing return on investment and cost savings over broader clinical benefits: “What is this generating for the company?” (Interviewee 13).

Alongside these financial concerns, there are infrastructure limitations that add complexity to system deployment via certified cloud or on-premise solutions: “If I’m putting in the cloud then I have to go some particular… telemetric… cloud services.” (Interviewee 15). Compliance with GDPR and data residency requirements, such as health data being restricted to national boundaries, necessitates the creation of “safe, bounded environments” or internal “gardens” (Interviewee 6). These technical hurdles, combined with limited access to hospitals, lead to significant friction losses, so that the implementation of AI is as much a challenge of logistics and financial planning as it is of clinical science.

4.2.3 Engaging in Grassroots Experimentation and Shadow AI Use

This subsection describes how participation in grassroots experimentation and shadow ai use characterize a decentralized, clinician-led adoption landscape. Firstly, bottom-up experimentation illustrates how physicians and residents initiate the use of AI themselves, employing self-taught methods and recommendations from colleagues to integrate the technology into their daily workflows: “AI adoption is thus bottom-up driven.” (Interviewee 1). These informal tests often involve the use of free AI tools to validate guideline scenarios or to evaluate anonymized diagnostic lists: “I used ChatGPT privately to describe findings.” (Interviewee 8).

On the other hand, since top-down directive mandates imposed without consultation with the workforce lead to friction losses in the workflow, the organic efforts described above often encounter implementation difficulties: “It’s top-down… things are bought and we are told: learn this now." (Interviewee 7), and sometimes necessitate manual "copy-paste" workarounds: "We have to copy-paste the medications into the discharge letter." (Interviewee 5). Such structural disconnects foster "shadow AI", the unofficial deployment of public tools and private devices: "If we don't regulate what's used, people say: I'll just use my own GPT-5." (Interviewee 3). While following the "path of least resistance" facilitates immediate problem-solving, it bypasses institutional governance, introducing compliance and data security risks: "One might use DeepSeek, another Perplexity… what you put in there feeds the big model." (Interviewee 6). Collectively, these results highlight a significant tension between institutional strategy and the pragmatic, self-directed technological integration taking place on the clinical front, where informal consultations often precede formal implementation.

4.2.4 Navigating Hype-Driven Adoption and Pilot Experimentation

The findings regarding hype-driven adoption and pilot projects highlight the tension between speculative enthusiasm and pragmatic clinical integration. With regard to hype-driven adoption, AI is described as "today's fancy word", where a "fear of missing out" and "gold rush" funding drive rushed deployments: "Today's flavor… Let's get AI in everything." (Interviewee 2). These speculative efforts often lead to the introduction of "toys" or an "echo chamber of success stories" that are detached from medical reality (Interviewee 13).

Conversely, the data on the topic of problem-first vs. tool-first AI implementation show a critical attitude towards ROI-driven, "tool-first" approaches that ignore existing clinical workflows: "They choose the tool first and then try to work backwards to the business case." (Interviewee 3). This "shortcut mentality" often leads to high project failure rates, suggesting that successful adoption requires grounding in specific "clinical pain points" rather than abstract narratives: "Studies say around 90% of AI projects fail because people look for a blueprint." (Interviewee 3). Finally, pilot experimentation emphasizes "learning by doing" through small, iterative projects: "Early validation in pilot hubs..." (Interviewee 12). By using pilot projects to experience rapid failure and validate initial results, organizations can manage uncertainty and build acceptance. This shifts the focus from speculative promises to empirically grounded clinical findings: "We must learn by doing and by failing… 'failing fast,' the classic words." (Interviewee 6).

4.3 Legitimation

The "Legitimation" dimension describes how organizations attempt to make the use of AI in clinical settings acceptable and justifiable. This legitimacy work focuses on clinical validation, formal governance structures, and practical safeguards that prevent errors and misuse. In many cases, compliance with data protection regulations serves as an everyday check and balance. Human oversight remains an indispensable prerequisite, especially given the inherent opacity of AI systems. By integrating risk classification and explainable AI, organizations foster trust and ensure accountability, bridging the gap between technological innovation and professional clinical responsibility.

4.3.1 Addressing AI Errors and Demanding Clinical Validation

Respondents described a tension between AI's promise to reduce errors and its current limitations. Model errors, including hallucinations and limitations, pose a major problem, as AI can misclassify rare patterns, such as mistaking a button for a tumor or issuing irrelevant warnings: "AI has never been trained what a button looks like… said it was… a tumor." (Interviewee 2). These problems require targeted, domain-specific training to improve currently perceived accuracy: "It's a matter of time until it gets better." (Interviewee 8).

At the same time, AI was positioned as a potential factor in reducing diagnostic errors, especially when trained with very large datasets: "With 50 million skin cancer images, AI has higher hit rates." (Interviewee 11). For some clinicians, this represents a responsibility argument for implementation if the results demonstrate a meaningful improvement: "Ethically wrong to withhold AI if it is better." (Interviewee 8). Finally, rigorous clinical validation is needed to close the evidence gap regarding practical implications: "You'll see thousands of papers saying… great… and… no value… no one's collected that data yet." (Interviewee 2). This emphasizes support for pre-implementation testing and ongoing monitoring for deviations, prioritizing quantified evidence over intuition: "Instead of gut feeling, I want evidence-based data showing where we stand and what to do." (Interviewee 3).

4.3.2 Establishing AI Governance Structures and Risk Oversight

The data suggest a shift from informal accountability to more formalized governance. Respondents reported gaps in documentation and unclear responsibilities, particularly where no defined lifecycle governance exists: "There is nowhere documented that we may use it or rely on it." (Interviewee 4). In response, organizations are creating control structures that assign responsibilities and enable regular reviews. One participant described a multi-tiered system with designated contact persons for all clinical and operational functions: "There are two contact persons… one medical and one nursing… for problems and wishes." (Interviewee 5).

Furthermore, daily risk management is facilitated by integrated safeguards, automated risk triggers and principles-based escalation, ensuring that governance functions as a continuously evolving mechanism for patient safety: “Escalation follows defined principles.” (Interviewee 12). In gray areas, interviewees often reported a low tolerance for risk: “Even if it’s a little bit on the grey area… we are not taking the chance.” (Interviewee 13). This is supported by risk classification frameworks that categorize systems according to sensitivity and agency and must differentiate between passive and proactive AI: “You have to start bucketing it… each… has different regulations and different ethical issues.” (Interviewee 2). Through the use of structured impact assessments and joint medical-technical evaluations, these structures aim to balance innovation value with safety and to ensure that ethical, legal and regulatory aspects are integrated throughout the entire AI lifecycle: “Physicians and technical teams jointly evaluate.” (Interviewee 12). Taken together, these practices aim to transform governance from a perceived bottleneck into a stabilizing element of clinical quality assurance.

4.3.3 Embedding Ethical Reflection and Building Trust

Ethical reflection and trust-building were described as essential, but inconsistently institutionalized. Some respondents emphasized that responsibility must shape design decisions, including data restrictions and governance requirements: “Higher data and governance requirements.” (Interviewee 12). This involves rigorous “member checking” via review boards and scrutinizing data for bias to clarify the intended use of AI outputs: “They even put in place different review boards, different governance.” (Interviewee 13).

At the same time, trust is built through transparency: “I know they used tens of thousands of ECGs with cath films to train the AI.” (Interviewee 4) and educational strategies, for example, by using everyday analogies to reduce anxiety. Trust is fostered when clinicians develop tools together and maintain transparency regarding training data: “Some of the good companies doing it well… consulting very deeply with their users.” (Interviewee 2). Vice versa, overpromising leads to an erosion of institutional credibility: “People stop believing in AI after bad experiences.” (Interviewee 14). Despite the importance placed on ethics, several accounts indicate that reflection is often neglected due to lack of time and reduced to data protection. One interviewee described ethics as lagging behind implementation: “The framework always comes later in Germany… ethical principles and legislation are missing.” (Interviewee 7). This tension underlines the need for formalized spaces for reflection throughout the entire AI lifecycle.

4.3.4 Complying with Data Privacy Regulations and Security Requirements

In the interviews, data protection and data security proved to be practical control mechanisms for clinical AI. Compliance with the GDPR and its associated localization requirements was described as essential, and in some cases, IT departments actively blocked the use of external tools for sensitive data: “Our IT blocked it: these are sensitive data, we can’t just throw them into some AI.” (Interviewee 5). Security concerns were also interpreted culturally as a kind of “digital paranoia” triggered by fears of data leaks and potential misuse, for example in the insurance sector: “The company was paranoid… no WiFi… we weren’t allowed to use WhatsApp.” (Interviewee 6).

Respondents also pointed to a broader regulatory environment, including the Medical Device Regulation (MDR) and the EU AI-Act, and characterized the healthcare sector as highly regulated: “In the Healthcare is like one of the biggest regulations in the world.” (Interviewee 15). While these regulations guarantee safety, the enforcement of the rules and the perceived strictness of European practice can lead to a structural disadvantage, which manifests itself in slowness compared to other global players: “In Europe I see like there are lots of regulations… process is very slow.” (Interviewee 15). By prioritizing compliance over rapid innovation, these structures oblige technology providers to localize models within constrained environments: “Regulatory compliance take precedence.” (Interviewee 12). Ultimately, managing the tension between transparency, vulnerability, and speed remains a crucial challenge in an environment where data is increasingly accessible but still susceptible to data breaches.

4.3.5 Maintaining Human Oversight Amid Black-Box Opacity

The question of maintaining human oversight in the face of opaque systems establishes the principle of “human in the control loop” as a crucial ethical and clinical safeguard: “We can never offload responsibility. We are ultimately responsible.” (Interviewee 4). AI is therefore positioned as a supporting tool (“idea generator”), not as an autonomous decision-maker: “Viewing AI primarily as supportive knowledge rather than decision-making automation.” (Interviewee 1). This oversight includes strict plausibility checks and the ability to override AI suggestions if they contradict the clinical context: “Machines miss rare things; humans must check.” (Interviewee 8). The participants also emphasized that the decision-making authority remains with the doctors and is based on case-specific considerations and patient safety: “Physicians rely on their expertise and maintain decision authority.” (Interviewee 1).

These measures directly address the challenges of the lack of transparency in AI systems, whose opaque functioning of neural networks can make accountability difficult and undermine user trust: “With neural networks… you don’t know what is happening inside.” (Interviewee 13). Explainable AI has therefore been described as increasingly important, including mechanisms such as justification logs and localized reasoning, which make the results more interpretable: “It gives you a justification… why this is the outcome of this process.” (Interviewee 13). Ultimately, maintaining human judgment ensures that clinical practice continues to be based on irreplaceable professional experience, despite the increasing influence of probabilistic machine predictions.

4.4 Reconfiguration

The “Reconfiguration” dimension describes systemic transformations through the development of AI competencies and the promotion of cross-functional collaboration to overcome training gaps and cultural barriers. It encompasses managing job losses by shifting from fear of replacement to complementary care models. By accepting the inevitability of AI, the focus of healthcare shifts toward supportive platforms where clinicians act as central coordinators, effectively redesigning professional roles and diagnostic pathways to ensure the survival of the system.

4.4.1 Developing AI Literacy and Addressing Training Gaps

Respondents described AI literacy as a long-term necessity, not a one-off training measure. Some formulated specific goals for comprehensive competence development: “My North Star is contributing to AI literacy by 2030.” (Interviewee 3). Others emphasized the need to help clinicians understand where AI is useful and how to work with it: “How this technology can be useful? We have to spread that thing.” (Interviewee 15). This includes internal discussions, self-study, and specialized training through professional associations such as the German Society for Radiology: “They offer certificates to teach basics of AI.” (Interviewee 8).

At the same time, respondents reported persistent gaps. One-off training sessions offered by providers were frequently described as inadequate, leaving clinicians reliant on informal exchanges with colleagues: “It is trained once… the rest you somehow have to manage yourself.” (Interviewee 7). Some participants also criticized the fact that the training prioritizes medical and legal formalities over practical clinical application. A broader “educational vacuum” was described, in which curricula lag behind clinical reality, forcing educators and organizations to create their own content: “I questioned whether the training reflects reality or just covers medico-legal aspects." (Interviewee 4). To address these shortcomings, those involved are advocating for protected time slots and the integration of practical experience into formal schooling: "We need experts who come and teach us… different perspectives." (Interviewee 7). Overall, the data suggest that while skills development is generally recognized as crucial, the current educational infrastructure remains fragmented and inconsistent.

4.4.2 Fostering Cross-Functional Collaboration and Cultural Support

The data further suggests that systemic synergies form the basis for successful AI integration. Cross-functional teams play a central role in this: "The real answer is to build a heterogeneous team that works from business cases." (Interviewee 3). They ensure a holistic 360-degree view to reduce biases and build internal communities of practice: "I need people who burn for this, build a community in the organization." (Interviewee 3). Such collaboration is further strengthened by having different areas of expertise represented in the management bodies in order to ensure comprehensive evaluation and oversight.

Leadership and corporate culture proved to be a conducive foundation. Several respondents argued that support from the management level was necessary to prevent paralysis and to secure resources, for example by providing dedicated budgets for pilot projects: "I'd put it at the CEO level… ring-fence a budget for projects." (Interviewee 6). Supportive leadership must provide guidance in uncertain times and integrate AI goals into management objectives to align board investments with grassroots enthusiasm: "It needs leadership that believes we need it, then we take people with affinity for pilot projects." (Interviewee 6). The results ultimately underline the role of bridge builders who provide a twofold translation between technical results and meaningful medical contexts: "I have to convert the technical means output in terms of the medical context." (Interviewee 15). This translation works both ways: "Convert my technical words into the medical contacts and… medical to… technical world." (Interviewee 15). In these representations, progress depends as much on shared expertise and cultural support as on the underlying models.

4.4.3 Confronting Job Displacement and Shifting Care Models

Confronting the fear of job losses and changing care models reveals a profound transformation of professional roles and structures in the healthcare sector. A central point of contention is the debate surrounding the expansion or replacement of skilled workers: "I think the solution becomes human augmentation, not replacement for the next 10 years." (Interviewee 2), highlighting a tension between AI as a supportive "human-in-the-loop" tool and the fear of upheavals in non-invasive specialties such as radiology and dermatology: “Everything non-invasive will more or less disappear.” (Interviewee 11). While manual and invasive specialties remain resilient, the shift of analytical tasks to machines requires clinicians to reflect on their own abilities in order to maintain their competitive edge in terms of creativity: “Manual work like catheterization is less replaceable.” (Interviewee 10).

Beyond individual roles, the respondents also expressed concerns about the general market structure. One described the competition as asymmetrical, with smaller companies struggling against larger providers: “It’s David against five Goliaths.” (Interviewee 14). According to him, this imbalance could be balanced through taxation and redistribution. Another linked displacement risk to possible regulation mechanisms intended to slow replacement: “Some kind of regulation… may block… replacing people.” (Interviewee 13). In addition to these concerns, the respondents described a shift in care models towards more supportive, platform-like structures: “Shift from AI products to an enablement model.” (Interviewee 12). This transition changes diagnostic pathways, positions general practitioners as central coordinators of AI-supported care: “The GP will benefit extremely… gets the specialist report.” (Interviewee 10), and enables a significant expansion of the physician patient groups: “One physician can probably take care of 100,000 patients rather than only 2000.” (Interviewee 9).

A final factor influencing these forecasts is the perceived system load. Several reports described AI as increasingly necessary, as the current model is on the verge of collapse: “We’re at a breaking point with the old model of healthcare.” (Interviewee 9). Demographic change has been repeatedly cited in this context: “Baby boomer… every year we’re losing people… AI is definitely going to become mandate.” (Interviewee 2). The complexity of transparency is ultimately underscored by the involvement of patients, as clinicians must weigh the risks of patient-centered research. While this is sometimes appropriate and helpful: “They sometimes also are right and have helpful ideas.” (Interviewee 4), it also carries risks if patients act on AI results without clinical supervision: “… I take the medicines… from the AI prescribe me which may be harmful for me.” (Interviewee 15). Overall, these results suggest that AI simultaneously raises concerns about displacement and enables systemic restructuring by shifting roles, expanding coordination, and creating new skill requirements.

5 Discussion

Chapter 4 shows that the implementation of RBMI in the context of AI adoption is a complex and controversial organizational process. With regard to the four dimensions of Augmentation, Embedding, Legitimation, and Reconfiguration, the results confirm and extend the integrated framework developed in Chapter 2. This framework, which synthesizes BMI, RI, RBMI, and RAI, assumes that responsible transformation requires the translation of normative RI principles into organizational mechanisms (RBMI) and concrete business model design (RBMC), while addressing the challenges posed by AI as a catalyst technology. The analyzed data from the European healthcare sector shows that this translation process is neither linear nor secure but rather a contested, iterative, and context-dependent practice fraught with tensions between technological potential, economic necessities, and ethical-social responsibilities.

5.1 Augmentation in AI-Enabled Business Model Innovation

The Augmentation dimension directly manifests the core message (from sections 2.4.1 and 2.4.2) that AI acts as a transformative general-purpose technology and catalyzes BMI by enabling novel value creation and delivery mechanisms. The data confirms that AI is not being used abstractly but rather for concrete, value-creating use cases that reconfigure activity systems. Applications in diagnostic imaging (e.g., AI as a “second reader” in radiology, volumetry), the automation of clinical documentation (LLM-supported note generation), and information retrieval for evidence synthesis. These use cases correspond to what previous work describes as AI-enabled augmentation and automation of BMs (Sjödin et al., 2023). They also align with the BMI perspective that innovation resides in the architectural reconfiguration of “what, how, and for whom” value is created (Aagaard, 2024). For instance, AI-supported diagnostics shift the “how” of value delivery by integrating machine vision into the diagnostic pathway, while administrative automation reallocates costly clinician time from bureaucratic tasks to actual patient care, thereby changing the cost structure and the value proposition.

However, the data also put this technological view into perspective. Augmentation is primarily driven by immediate clinical and operational challenges such as overwhelming data volumes, documentation burdens, and staff shortages, and not by a strategic, top-down mandated vision for BMI, which is often triggered by external pressure and implemented through iterative experimentation (Aagaard, 2024). In this sense, value creation in the initial phase often emerges organically and begins with grassroots experiments initiated by clinicians. The initial impetus for AI-enabled BMI in healthcare therefore seems to lie less in pursuing radically new business model archetypes but rather in stabilizing service delivery within already strained models.

5.2 Embedding Responsible Business Model Innovation under Constraints

The Embedding dimension exposes that a central tension at the core of RBMI theory lies in the fact that the innovation processes clash with deeply ingrained organizational logics that prioritize efficiency and short-term economic profitability (Hope, 2018; Hope and Moehler, 2015). Time pressure, skills shortages, and financial constraints jointly create a paradox. Workforce shortages act as a strong external driver for AI adoption, aligning with RBMI's response to societal challenges. At the same time, the resulting scarcity of time and resources undermines the reflective, inclusive, and future-oriented practices required for RI.

Theoretically, RI and RBMI emphasize the anticipation of unintended consequences and the involvement of stakeholders (Magni et al., 2024; Stilgoe et al., 2013). However, the results show that “time scarcity” functions as a primary barrier. Excessive workload limits the possibilities for structured implementation, joint reflection, and ethical consultation. Similarly, “budget myopia” and a lack of reimbursement mechanisms favor cost-effective, short-term solutions, leading to a “cheapest-solution” tendency that directly contradicts the RBMI mechanism of CSRV (Magni et al., 2024). This indicates that the theoretical assumption that economic viability is a necessary prerequisite for RBMI (Hope, 2018) is often interpreted in practice in a one-sided and short-term financial manner. This can hinder responsible practices from the outset.

The topics of grassroots experiments and hype-driven takeovers illustrate the governance gap discussed in section 2.4.4, which manifests itself in low operational RAI maturity. The proliferation of “shadow AI” reflects limited innovation capability and governance structures that have not kept pace with the availability of AI tools. Decentralized, grassroots-oriented use often bypasses formal review and ethics processes that are central to RAIG. As a result, a gap emerges between de jure governance frameworks like the EU AI Act and de facto clinical practice. This challenges the assumption of orderly, top-down implementation and instead points to a fragmented reality that calls for more adaptive and responsive governance arrangements. This reality challenges the orderly, top-down translation of ethical and regulatory logics into RAIG structures, as shown in Figure 5, and instead points to a fragmented reality that calls for more adaptive and responsive governance arrangements.

5.3 Legitimation through Responsible AI Governance

The Legitimation dimension offers the most direct insight into how RAI and RAIG principles are operationalized in the context of European healthcare. The findings map closely onto the seven requirements for trustworthy AI (Table 3) and reveal both progress and remaining shortcomings in AI-driven business model innovation. Practices such as addressing AI errors and insisting on rigorous clinical validation put the principles of technical robustness, safety, and accountability into practice. The tension between AI's potential for error reduction and the need for domain-specific validation reflects a shift from compliance-driven governance to evidence-based management.

The establishment of AI governance structures underscores the theoretical necessity of RAIG as a continuous process of sensing, adapting, and integrating (Papagiannidis et al., 2025). The described shift from “systemic accountability gaps” to “strategic oversight bodies” and “integrated guardrails” illustrates how organizations develop structural and procedural practices, which is considered essential for implementing RAI principles in practice. The development of “risk classification frameworks” for AI systems demonstrates an organizational learning process that aligns with the RI dimension of reflexivity, as organizations develop a more nuanced understanding of the ethical and operational profiles of various AI applications.

Despite this progress, the results also highlight a significant limitation. While the GDPR functions as an effective “practical gatekeeper”, in-depth ethical reflection is often “reduced to data protection” due to a “lack of time for societal reflection”. This confirms the theoretical critique that operational RAI maturity often lags behind strategic commitment (Brynjolfsson and McAfee, 2017; Maslej et al., 2025). Although trust is theoretically based on joint development and transparency regarding training data, these practices remain inconsistent and unsystematic in practice.

Across the Legitimation dimension, human oversight emerges as the central boundary condition. Clinicians consistently reject the idea of delegating responsibility to AI systems and instead see AI as a supporting knowledge tool and not as an autonomous decision-maker. This sets a fundamental ethical and clinical boundary and addresses the central challenge of black box technology, where humans do not know exactly how the AI works. The emphasis on explainability reinforces the view that responsibility in the field of AI does not lie solely with algorithms, but arises from socio-technical interactions between systems, experts, and organizational structures (Zimmer et al., 2022).

5.4 Reconfiguration toward Systemic Responsible Innovation

The Reconfiguration dimension captures longer-term, systemic implications of AI adoption that extend beyond individual applications. These include shifts in professional roles, care models, and organizational capabilities. This aligns with the transformative potential of AI-powered BMs discussed in section 2.4.2 and the drivers outlined in section 2.5. The call for continuous skill development and the criticism of institutional gaps in formal AI education underscore that the mere introduction of technologies is insufficient. Developing BMI competence requires raising awareness of design problems and defining them, specifically tasks that are made more difficult by current educational deficits (Zott et al., 2024). This human capital challenge is a crucial internal prerequisite for successful RBMI.

Promoting cross-functional collaboration confirms the theoretical assumption that successful BMI and RAI require bridging different areas of knowledge. The need for heterogeneous teams, bridge builders between the technical and clinical worlds, and a leadership that recognizes this need for AI augmentation echoes the internal drivers of leadership and culture. It demonstrates that the RBMI mechanism of RKE is enacted through concrete collaborative practices. Most profoundly, confronting job displacement and shifting care models engages with the ultimate societal impact of AI-driven BMI. The tension between “augmentation versus replacement” and the vision of a shift “from product-oriented care to supportive platforms” indicates a reconfiguration of the very architecture of healthcare delivery. This aligns with the theoretical outcome of industry model innovation, redefining or creating new industry segments (Zott et al., 2024). The frequent portrayal of AI as an “inevitable necessity” to prevent systemic collapse under demographic pressure further links external factors with internal change. In this context, RBMI appears to be motivated less by a proactive pursuit of responsible innovation and more by the reactive need to maintain the system’s functionality. Responsibility thus functions both as a constraint and a prerequisite for socially acceptable change.

5.5 Theoretical Integration and Practical Implications

Taken together, the findings portray that the process of implementing RBMI with AI is a deeply dialectical one. The theoretically neat integration of RI dimensions into BMI architecture (Table 1) is, in practice, a site of constant negotiation. Augmentation provides the technological dynamics for the transformation of value creation and delivery. Embedding exposes the frictional interface where responsible aspirations meet the inertial forces of existing economic and temporal logics. Legitimation represents the institutional work of building governance structures to manage risk and align with ethical-regulatory demands, a process that is both formal, through its committees and guidelines, and informal, because it also depends on building trust and maintaining oversight. Finally, Reconfiguration points toward the emergent long-term outcomes, such as new capabilities, evolving roles, and emerging supply models, that could shape the responsible business model of the future.

A key conclusion is that responsibility cannot be added retroactively. It must be integrated into design decisions from the outset. However, the data indicate that the assumption of responsibility is often uneven and insufficiently coordinated. It is often driven more by practical necessities (e.g., GDPR compliance) and professional ethical principles (e.g., the physician's duty of care) than by conscious strategic planning. The RBMI framework therefore appears less as a binding guideline but rather as an awareness-raising tool that clarifies the underlying mechanisms, tensions, and trade-offs. The results also suggest that, in order to more comprehensively explain real-world phenomena, RBMI theory needs to more strongly incorporate the role of frontline action, including shadow AI practices and grassroots experimentation, as well as the paralyzing effect of resource constraints on ethical deliberation. To translate these insights into action, the study proposes a practical framework for managers dealing with AI-enabled RBMI, structured around the four core dimensions (see Figure 8).

Author's own compilation.

Figure 8. Framework for Responsible AI Integration

This framework does not offer a linear blueprint but a set of interdependent priorities that help practitioners deal with the tensions observed in this study. The overarching message is that responsible integration depends as much on how organizations act, learn, and coordinate as it does on the technology itself. Ultimately, the journey toward responsible AI-enabled BMs in healthcare is shown to be a collective, contested, and unfinished project of aligning technological possibility with professional virtue and social legitimacy.

6 Conclusion

This dissertation investigated how AI-driven RBMI is implemented in the European healthcare sector. Based on an integrated framework combining BMI, RI, RBMI, and RAI, the study examined this phenomenon. Using a qualitative, single instrumental case study design, the research reveals that the journey toward responsibility does not follow a linear or prescriptive trajectory. Rather, it evolves as a contested and iterative process characterized by ongoing tensions between technological possibilities, economic and operational constraints, ethical imperatives, and professional norms.

Across the four dimensions of Augmentation, Embedding, Legitimation, and Reconfiguration, the findings indicate that AI acts as a catalyst for a value reconfiguration driven more by immediate clinical and systemic constraints than by abstract strategic visions. The integration of responsibility, operationalized through the RI dimensions of anticipation, reflexivity, inclusion, and responsiveness, encounters significant friction. In particular, the Embedding dimension reveals a central paradox, as external factors such as labor shortages necessitate the adoption of AI, while internal constraints such as lack of time and "budget myopia" hinder the reflective, inclusive, and future-oriented practices that are essential for RBMI. This leads to a gap between normative theory and practical implementation, where responsibility is often reduced to compliance with data protection regulations rather than being an integral part of the innovation process.

The study further underscores that responsibility in AI-enabled transformation cannot be an afterthought but must function as a constitutive design principle. This is most evident in the legitimacy dimension, where the unwavering insistence on human oversight and clinical validation sets a fundamental ethical limit. Trust and accountability are built not through algorithms alone but through sociotechnical interactions, transparent governance, and the co-design of tools with end-users. Ultimately, the research suggests that in healthcare, the drive toward RBMI may be less a proactive pursuit of leadership in responsible innovation and more a reactive necessity for systemic survival amid demographic and resource crises. Responsibility thus serves as both a crucial constraint and a vital enabler of socially acceptable transformation.

6.1 Limitations

This study has several limitations that should be considered when interpreting its findings. First, the research is contextually bounded, focusing exclusively on the European healthcare sector. The EU single market, strong regulatory environment, and specific institutional pressures may limit the direct transferability of findings to regions with different regulatory landscapes and healthcare systems. Second, while the qualitative, exploratory study design and the use of a purposive expert sample allow for rich and differentiated insights, they do not permit statistical generalization. The perspectives captured, though diverse, may not represent the full spectrum of experiences across all healthcare organizations. Third, the study captures a snapshot in time during a period of rapid technological and regulatory evolution. The dynamics of AI adoption and governance are fluid, meaning the described practices and tensions may shift considerably in the coming years.

6.2 Future Research

The results open up several promising avenues for future scientific research. First, comparative studies across different sectors and geographical regions could demonstrate how varying levels of regulation, market structures, and cultural norms influence the implementation of AI-powered RBMI. Second, longitudinal research is needed to track the evolution of organizations' governance structures and business models over time, from initial experiments to mature, scaled implementation of responsible AI. Third, while this study focused on the organizational level, future research could examine the micro-foundations of RBMI and analyze the individual cognitive frameworks, ethical reasoning, and practices of managers, physicians, and data scientists who implement responsible innovation on a daily basis. Finally, design research is needed to develop and test practical tools, frameworks, and interventions that help organizations manage the identified areas of tension. These could include, for example, instruments for ethical decision-making under time pressure or cost-benefit models for long-term, responsible investments. This could bridge the critical gap between RBMI theory and practice. In conclusion, this dissertation contributes a grounded, nuanced understanding of the complex process of aligning AI-driven BMI with societal expectations and ethical stewardship. It reaffirms that the path to RI is neither easy nor safe but rather an essential, collaborative endeavor for organizations that want to harness the power of technology without compromising their social legitimacy or core values.

Bibliography

Aagaard, A., 2024. Introducing Business Model Innovation and the Game Changers of Tomorrow, in: Aagaard, A. (Ed.), Business Model Innovation. Springer International Publishing, Cham, pp. 1–25. https://doi.org/10.1007/978-3-031-57511-2_1

Aagaard, A., Tucci, C., 2024. AI-Driven Business Model Innovation: Pioneering New Frontiers in Value Creation, in: Aagaard, A. (Ed.), Business Model Innovation. Springer International Publishing, Cham, pp. 295–328. https://doi.org/10.1007/978-3-031-57511-2_10

Åström, J., Reim, W., Parida, V., 2022. Value creation and value capture for AI business model innovation: a three-phase process framework. Rev Manag Sci 16, 2111–2133. https://doi.org/10.1007/s11846-022-00521-z

Balcioğlu, Y.S., Çelik, A.A., Altindağ, E., 2025. A turning point in AI: Europe's human-centric approach to technology regulation. Journal of Responsible Technology 23, 100128. https://doi.org/10.1016/j.jrt.2025.100128

Black, S., Samson, D., Ellis, A., 2024. Moving beyond 'proof points': Factors underpinning AI-enabled business model transformation. International Journal of Information Management 77, 102796. https://doi.org/10.1016/j.ijinfomgt.2024.102796

Bocken, N.M.P., Short, S.W., Rana, P., Evans, S., 2014. A literature and practice review to develop sustainable business model archetypes. Journal of Cleaner Production 65, 42–56. https://doi.org/10.1016/j.jclepro.2013.11.039

Bouderhem, R., 2024. Shaping the future of AI in healthcare through ethics and governance. Humanit Soc Sci Commun 11, 416. https://doi.org/10.1057/s41599-024-02894-w

Brynjolfsson, E., McAfee, A., 2017. The business of artificial intelligence: What it can and cannot do for your organization. Harvard Business Review 7, 3–11.

Butt, J.S., 2024. Analytical Study of the World's First EU Artificial Intelligence (AI) Act, 2024. International Journal of Research Publication and Reviews Vol 5, 7343–7364.

Creswell, J.W., Poth, C.N., 2018. Qualitative Inquiry & Research Design: Choosing among Five Approaches, Fourth Edition. ed. SAGE Publications, Inc., Los Angeles, CA.

European Commission, 2021. Annexes to the Communication 'Fostering a European approach to Artificial Intelligence,' COM(2021) 205 final.

European Parliament and Council, 2024. EU Artificial Intelligence Act, Regulation (EU) 2024/1689. Official Journal of the European Union (OJ).

Fatima, S., Desouza, K.C., Buck, C., Fielt, E., 2021. Business Model Canvas to Create and Capture AI-enabled Public Value, in: Hawaii International Conference on System Sciences 2021. Presented at the Hawaii International Conference on System Sciences, University of Hawai'i at Manoa, Hamilton Library, Honolulu, HI, pp. 2317–2326.

Ferdelman, M.H., Mehta, D., Owens, T., 2025. Artificial Intelligence: In-Depth Market Analysis (Market Insights Report). statista.

Foss, N.J., Saebi, T., 2018. Business models and business model innovation: Between wicked and paradigmatic problems. Long Range Planning 51, 9–21. https://doi.org/10.1016/j.lrp.2017.07.006

Foss, N.J., Saebi, T., 2017. Fifteen Years of Research on Business Model Innovation: How Far Have We Come, and Where Should We Go? Journal of Management 43, 200–227. https://doi.org/10.1177/0149206316675927

Füller, J., Hutter, K., Wahl, J., Bilgram, V., Tekic, Z., 2022. How AI revolutionizes innovation management – Perceptions and implementation preferences of AI-based innovators.

Technological Forecasting and Social Change 178, 121598. https://doi.org/10.1016/j.techfore.2022.121598

Geissdoerfer, M., Savaget, P., Bocken, N.M.P., Hultink, E.J., 2017. The Circular Economy – A new sustainability paradigm? Journal of Cleaner Production 143, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

Gibson, K., 2024. AI-Driven Business Models: 4 Characteristics. Harvard Business School | Online | Business Insights. URL https://online.hbs.edu/blog/post/ai-driven-business-models (accessed 10.6.25).

Gioia, D.A., Corley, K.G., Hamilton, A.L., 2013. Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. Organizational Research Methods 16, 15–31. https://doi.org/10.1177/1094428112452151

Häußermann, J.J., Lütge, C., 2022. Community-in-the-loop: towards pluralistic value creation in AI, or—why AI needs business ethics. AI Ethics 2, 341–362. https://doi.org/10.1007/s43681-021-00047-2

Herrmann, H., 2023. What's next for responsible artificial intelligence: a way forward through responsible innovation. Heliyon 9, e14379. https://doi.org/10.1016/j.heliyon.2023.e14379

High-Level Expert Group on AI, 2019. Ethics Guidelines for Trustworthy AI. Independent expert group set up by the European Commission, Brussels.

Holst, L., Mayer, V., Lämmermann, L., Urbach, N., Wendt, D.H., 2024. The Impact of the EU AI Act's Transparency Requirements on AI Innovation, in: International Conference on Wirtschaftsinformatik. Presented at the 19th International Conference on Wirtschaftsinformatik, Würzburg, Germany.

Hope, A., 2018. Sustainable Business Model Design: A Review of Tools for Developing Responsible Business Models, in: Moratis, L., Melissen, F., Idowu, S.O. (Eds.), Sustainable Business Models, CSR, Sustainability, Ethics & Governance. Springer International Publishing, Cham, pp. 377–394. https://doi.org/10.1007/978-3-319-73503-0_17

Hope, A., Moehler, R.C., 2015. Responsible Business Model Innovation: Reconceptualizing the role of business in society, in: EURAM 2015. Presented at the 15th Annual Conference of the European Academy of Management, Warsaw, Poland.

Jorzik, P., Antonio, J.L., Kanbach, D.K., Kallmuenzer, A., Kraus, S., 2024a. Sowing the seeds for sustainability: A business model innovation perspective on artificial intelligence in green technology startups. Technological Forecasting and Social Change 208, 123653. https://doi.org/10.1016/j.techfore.2024.123653

Jorzik, P., Klein, S.P., Kanbach, D.K., Kraus, S., 2024b. AI-driven business model innovation: A systematic review and research agenda. Journal of Business Research 182, 114764. https://doi.org/10.1016/j.jbusres.2024.114764

Kilian, R., Jäck, L., Ebel, D., 2025. European AI Standards – Technical Standardisation and Implementation Challenges under the EU AI Act. Eur. j. risk regul. 1–25. https://doi.org/10.1017/err.2025.10032

Koski, E., Murphy, J., 2021. AI in Healthcare, in: Honey, M., Ronquillo, C., Lee, T.-T., Westbrooke, L. (Eds.), Studies in Health Technology and Informatics. IOS Press. https://doi.org/10.3233/SHTI210726

Kumar, P., Dwivedi, Y.K., Anand, A., 2023. Responsible Artificial Intelligence (AI) for Value Formation and Market Performance in Healthcare: the Mediating Role of Patient's Cognitive Engagement. Inf Syst Front 25, 2197–2220. https://doi.org/10.1007/s10796-021-10136-6

Loaiza-Bonilla, A., Thaker, N., Chung, C., Parikh, R.B., Stapleton, S., Borkowski, P., 2025. Driving Knowledge to Action: Building a Better Future With Artificial Intelligence–Enabled Multidisciplinary Oncology. Am Soc Clin Oncol Educ Book 45, e100048. https://doi.org/10.1200/EDBK-25-100048

Lüdeke-Freund, F., Wells, P., Aagaard, A., 2024. The Catalytic Role of Sustainability Transitions for Business Models, in: Aagaard, A. (Ed.), Business Model Innovation. Springer International Publishing, Cham, pp. 127–155. https://doi.org/10.1007/978-3-031-57511-2_5

Magnani, G., Gioia, D., 2023. Using the Gioia Methodology in international business and entrepreneurship research. International Business Review 32, 102097. https://doi.org/10.1016/j.ibusrev.2022.102097

Magni, D., Palladino, R., Papa, A., Cailleba, P., 2024. Exploring the journey of Responsible Business Model Innovation in Asian companies: A review and future research agenda. Asia Pac J Manag 41, 1031–1060. https://doi.org/10.1007/s10490-022-09813-0

Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J.C., Shoham, Y., Wald, R., Walsh, T., Hamrah, A., Santarlasci, L., Lotufo, J.B., Rome, A., Shi, A., Oak, S., 2025. The AI Index 2025 Annual Report. Institute for Human-Centered AI, Stanford University.

Owen, R., Stilgoe, J., Macnaghten, P., Gorman, M., Fisher, E., Guston, D., 2013. A Framework for Responsible Innovation, in: Owen, R., Bessant, J., Heintz, M. (Eds.), Responsible Innovation. Wiley, pp. 27–50. https://doi.org/10.1002/9781118551424.ch2

Palinkas, L.A., Horwitz, S.M., Green, C.A., Wisdom, J.P., Duan, N., Hoagwood, K., 2015. Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. Adm Policy Ment Health 42, 533–544. https://doi.org/10.1007/s10488-013-0528-y

Papagiannidis, E., Mikalef, P., Conboy, K., 2025. Responsible artificial intelligence governance: A review and research framework. The Journal of Strategic Information Systems 34, 101885. https://doi.org/10.1016/j.jsis.2024.101885

Pepin, M., Tremblay, M., Audebrand, L.K., Chassé, S., 2024. The responsible business model canvas: designing and assessing a sustainable business modeling tool for students and start-up entrepreneurs. IJSHE 25, 514–538. https://doi.org/10.1108/IJSHE-01-2023-0008

Saenz, A.D., Mass General Brigham AI Governance Committee, McCoy, T., Mantha, A.B., Martin, R., Damiano, R., Adair, D., Heaney, D., Sisodia, R., Park, L., Forsberg, R., Tuffy, G., Murphy, S., Dreyer, K., Jones, M., Cosier, H.J., Logan, M., Bundela, Y., Centi, A., Ting, D., You, J.G., Landman, A., Mishuris, R.G., 2024. Establishing responsible use of AI guidelines: a comprehensive case study for healthcare institutions. npj Digit. Med. 7, 348. https://doi.org/10.1038/s41746-024-01300-8

Santa-Maria, T., Vermeulen, W.J.V., Baumgartner, R.J., 2021. Framing and assessing the emergent field of business model innovation for the circular economy: A combined literature review and multiple case study approach. Sustainable Production and Consumption 26, 872–891. https://doi.org/10.1016/j.spc.2020.12.037

Sheikh, H., Prins, C., Schrijvers, E., 2023. Artificial Intelligence: Definition and Background, in: Mission AI, Research for Policy. Springer International Publishing, Cham, pp. 15–41. https://doi.org/10.1007/978-3-031-21448-6_2

Singla, A., Sukharevsky, A., Yee, L., Chui, M., Hall, B., 2025. The State of AI: Global survey | McKinsey [WWW Document]. URL https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (accessed 10.7.25).

Sjödin, D., Parida, V., Kohtamäki, M., 2023. Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. Technological Forecasting and Social Change 197, 122903. https://doi.org/10.1016/j.techfore.2023.122903

Stake, R.E., 1995. The Art of Case Study Research. Sage Publications, Thousand Oaks, CA.

Stilgoe, J., Owen, R., Macnaghten, P., 2013. Developing a framework for responsible innovation. Research Policy 42, 1568–1580. https://doi.org/10.1016/j.respol.2013.05.008

Suri, H., 2011. Purposeful Sampling in Qualitative Research Synthesis. Qualitative Research Journal 11, 63–75. https://doi.org/10.3316/QRJ1102063

Teece, D.J., 2010. Business Models, Business Strategy and Innovation. Long Range Planning 43, 172–194. https://doi.org/10.1016/j.lrp.2009.07.003

Toniolo, K., Masiero, E., Massaro, M., Bagnoli, C., 2020. Sustainable Business Models and Artificial Intelligence: Opportunities and Challenges, in: Matos, F., Vairinhos, V., Salavisa, I., Edvinsson, L., Massaro, M. (Eds.), Knowledge, People, and Digital Transformation, Contributions to Management Science. Springer International Publishing, Cham, pp. 103–117. https://doi.org/10.1007/978-3-030-40390-4_8

Ulnicane, I., 2022. Artificial intelligence in the European Union, in: The Routledge Handbook of European Integrations. Routledge, London, pp. 254–269. https://doi.org/10.4324/9780429262081-19

Våland, T., Heide, M., 2005. Corporate Social Responsiveness: European Management Journal 23, 495–506. https://doi.org/10.1016/j.emj.2005.09.005

Van Genderen, M.E., Kant, I.M.J., Tacchetti, C., Jovinge, S., 2025. Moving Toward Implementation of Responsible Artificial Intelligence in Health Care: The European TRAIN Initiative. JAMA 333, 1483. https://doi.org/10.1001/jama.2025.1335

Voegtlin, C., Scherer, A.G., 2017. Responsible Innovation and the Innovation of Responsibility: Governing Sustainable Development in a Globalized World. Journal of Business Ethics 143, 227–243.

Williams, M., Moser, T., 2019. The Art of Coding and Thematic Exploration in Qualitative Research. International Management Review Vol. 15, 45–55.

Zeb, S., Fnu, N., Abbasi, N., Fahad, M., 2024. AI in Healthcare: Revolutionizing Diagnosis and Therapy. ijmdsa 3, 118–128. https://doi.org/10.47709/ijmdsa.v3i3.4546

Zimmer, M.P., Minkkinen, M., Mäntymäki, M., 2022. Responsible Artificial Intelligence Systems Critical considerations for business model design. Scandinavian Journal of Information Systems 34, 113–162.

Zott, C., Amit, R., 2007. Business Model Design and the Performance of Entrepreneurial Firms. Organization Science 18, 181–199. https://doi.org/10.1287/orsc.1060.0232

Zott, C., Amit, R., Giesen, E., 2024. Business Model Innovation Capability: A Game Changer for Sustaining a Firm's Edge, in: Aagaard, A. (Ed.), Business Model Innovation. Springer International Publishing, Cham, pp. 27–56. https://doi.org/10.1007/978-3-031-57511-2_2

Zott, C., Amit, R., Massa, L., 2011. The Business Model: Recent Developments and Future Research. Journal of Management 37, 1019–1042. https://doi.org/10.1177/0149206311406265

List of abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
BM	Business Model
BMC	Business Model Canvas
BMI	Business Model Innovation
CBM	Circular Business Model
CSR	Corporate Social Responsibility
CSRV	Corporate Social Responsiveness
DL	Deep Learning
ECG	Electrocardiogram
EU	European Union
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
LLM	Large Language Model
MDR	Medical Device Regulation
ML	Machine Learning
RAI	Responsible Artificial Intelligence
RAIG	Responsible AI Governance
RBMC	Responsible Business Model Canvas
RBMI	Responsible Business Model Innovation
RI	Responsible Innovation
RKE	Reflective Knowledge Exchange

Glossary

Artificial Intelligence (AI)

A system's ability to interpret external data, learn from it, and apply those learnings to achieve defined goals through adaptive behavior. In this study, AI refers primarily to narrow AI applications, such as machine learning and large language models, used in healthcare for diagnostic, administrative, and operational support.

Augmentation (in AI-enabled BMI)

The use of AI to enhance human capabilities, such as clinical decision-making, documentation, or information retrieval, without fully automating or replacing professional judgment. It reflects a "human-in-the-loop" approach where AI acts as a supportive tool.

Black-Box Opacity

The lack of transparency or explainability in how certain AI models, particularly deep learning systems, arrive at outputs or decisions, creating challenges for accountability, trust, and clinical validation.

Business Model (BM)

A firm-centric, boundary-spanning system of interdependent activities that describes how an organization creates, delivers, and captures value. It reflects the underlying logic of value exchange between the organization, its customers, and other stakeholders.

Business Model Canvas (BMC)

A strategic management template composed of nine building blocks, including value propositions, customer segments, and revenue streams, used to visualize, design, and analyze a business model.

Business Model Innovation (BMI)

The process of making designed, novel, and non-trivial changes to the core elements of a business model or to the architecture linking these elements, often in response to technological, competitive, or societal shifts.

Circular Business Model (CBM)

A business model designed to support regenerative value creation by slowing, closing, narrowing, or regenerating resource loops, thereby aligning economic activity with environmental sustainability.

Corporate Social Responsiveness (CSRV)

An organizational mechanism within RBMI that enables proactive management of social and ethical challenges, shifting from reactive liability toward forward-looking care and impact stewardship.

Embedding (in AI adoption)

The organizational process of integrating AI tools into existing workflows, structures, and cultures, often characterized by tensions between top-down strategy, bottom-up experimentation, and systemic constraints such as time scarcity or budgetary limits.

Explainable AI (XAI)

AI systems designed to provide human-understandable justifications for their outputs, improving transparency, trust, and clinical usability, especially in high-risk healthcare contexts.

Gioia Methodology

A structured qualitative research approach used to develop grounded theory from interview data. It involves iterative coding stages: first-order concepts (informant-centric), second-order themes (theory-centric), and aggregated dimensions.

Human-in-the-loop

A design and governance principle ensuring that human oversight, interpretation, and final decision-making authority are retained in AI-supported processes, particularly in high-stakes or ethically sensitive contexts.

Legitimation (in AI governance)

The process through which AI systems gain organizational and social acceptance via clinical validation, ethical alignment, regulatory compliance, and the establishment of formal oversight structures.

Reflective Knowledge Exchange (RKE)

A learning mechanism within RBMI that encourages ongoing critical reflection on assumptions, values, and unintended consequences, fostering adaptive and ethically informed innovation practices.

Responsible AI (RAI)

The design, development, and deployment of AI systems in ways that are ethical, trustworthy, and aligned with societal values, emphasizing fairness, accountability, transparency, and human oversight.

Responsible AI Governance (RAIG)

The structural, procedural, and relational practices, such as ethics committees, risk assessments, and monitoring protocols, that organizations implement to ensure responsibility across the AI lifecycle.

Responsible Business Model Canvas (RBMC)

An expanded version of the Business Model Canvas that incorporates five additional components, such as mission-driven values, stakeholder inclusion, and impact measurement, to explicitly embed responsibility into business model design.

Responsible Business Model Innovation (RBMI)

The innovation of a business model that integrates ethical, social, and environmental considerations into its core architecture, moving beyond profit maximization to deliver sustainable value for a broad range of stakeholders.

Responsible Innovation (RI)

A transparent, interactive innovation process guided by the dimensions of anticipation, reflexivity, inclusion, and responsiveness, aiming to align technological development with societal needs and ethical norms.

Reconfiguration (in AI-enabled transformation)

The systemic and long-term changes in organizational roles, capabilities, partnerships, and care models resulting from the integration of AI, often leading to new value networks and professional practices.

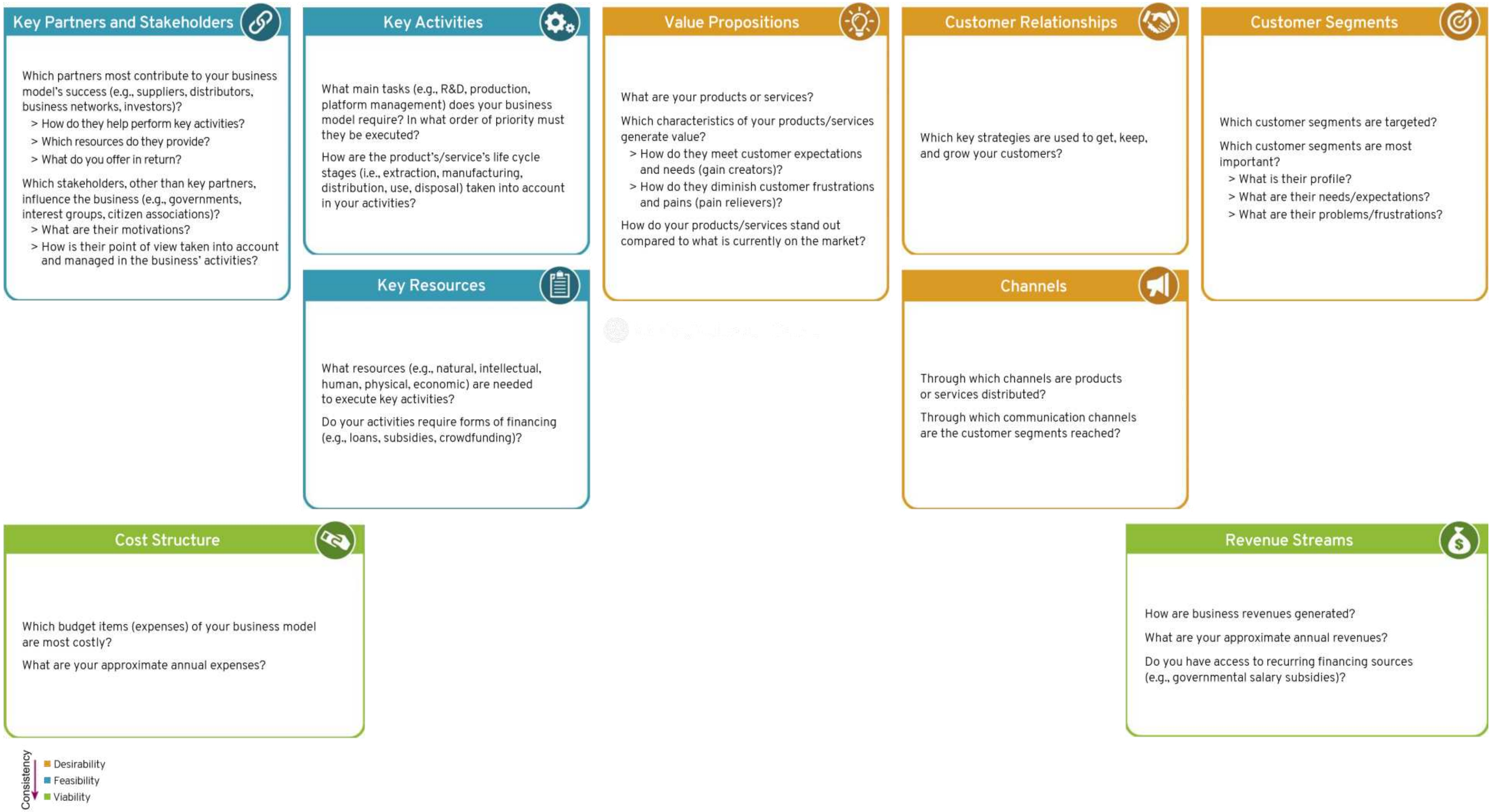
Shadow AI

The unofficial, unsanctioned use of AI tools—often publicly available platforms such as ChatGPT, by employees without formal organizational approval, raising issues of governance, data security, and compliance.

Stakeholder Inclusion

Integrating diverse perspectives into the design of business models to ensure that AI-supported innovations are aligned with societal values, ethical expectations, and long-term legitimacy among organizational and external stakeholders.

Appendix A - Business Model Canvas



Author's adaptation based on (Pepin et al., 2024).

Figure 9-A. Business Model Canvas

Appendix B - Responsible Business Model Canvas

Author's adaptation based on (Pepin et al., 2024).

Figure 10-A. Responsible Business Model Canvas

Appendix C - Semi-Structured Interview Guide

This interview guide explores how organizations implement responsible business model innovation when adopting AI, organized to move from general warm-up questions to core thematic domains and concluding reflections, while maintaining an inductive and non-leading question design. Topics for probing questions are marked with a "P".

#	Question
Warm-up	
1.	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context? *P: Responsibilities? Team interactions? Decision contexts? Stakeholder groups?* *Notes: Identify relevance of role to innovation, governance, or AI processes.*
External & Internal Drivers of AI Adoption	
2.	When your organization (or partners/clients) began working with AI, what factors most influenced this direction? *P: Triggering events? Strategic priorities? Emerging pressures/opportunities?* *Notes: Establish adoption rationale.*
3.	What external influences shape how AI is explored or adopted? *P: Regulatory expectations (GDPR, AI Act), accreditation, market trends, partner expectations, societal demands.* *Notes: Indicators of external drivers.*
4.	What internal conditions or capabilities affect how AI is approached? *P: Leadership signals, resources, digital maturity, culture, risk tolerance.* *Notes: Identify internal enablers/constraints.*
5.	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict? *P: Examples; trade-offs; escalation; decision routines.* *Notes: Look for tension management & value negotiation.*
Responsible Practices & Organizational Mechanisms	
6.	How does your organization or professional environment address responsibility, ethical questions, or societal impacts when working with AI? *P: Who raises concerns? How are they discussed?* *Notes: Responsibility framing; CSR/RI mechanisms.*
7.	How are potential impacts (clinical, operational, ethical, societal) explored before implementing AI-related changes? *P: Scenario analysis; foresight; risk identification.* *Notes: Anticipation practices.*
8.	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use? *P: Learning loops; reflection routines; critical review points.* *Notes: Reflexivity & RKE.*
9.	How are different groups or stakeholders involved in shaping AI-related decisions? *P: Clinicians, patients, managers, partners, boards, external experts.* *Notes: Inclusion & dialogue.*
10.	Can you describe how ethical or societal considerations influence daily work with AI? *P: Transparency, design choices, guardrails, operational constraints.* *Notes: Embedded CSRV practices.*
Governance of AI (RAI)	
11.	How is decision-making around AI organized in your organization or projects? *P: Roles, processes, cross-functional dynamics.* *Notes: Governance structure (formal/informal).*
12.	What structures, roles, or processes support oversight of AI-related activities? *P: Committees, model owners, boards, working groups.* *Notes: Governance architecture & maturity.*
13.	How do you assess, document, or monitor potential issues with AI systems over time? *P: Validation, audits, monitoring, lifecycle documentation.* *Notes: Lifecycle governance.*
14.	When difficult decisions arise (e.g. balancing clinical, operational, commercial, or ethical considerations) how are they handled? *P: Escalation, cross-functional dialogue, standards.* *Notes: Governance-in-action & accountability.*
Implications for Business Models	
15.	In what ways has AI influenced how value is created or delivered in your organization or sector? *P: New services; improved workflows; enhanced patient outcomes; changes in who receives value and how.* *Notes: Explicit coverage of value creation + value delivery.*
16.	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption? *P: New collaborations; capability development; data flows; integration issues.* *Notes: Covers value configuration.*
17.	How do considerations of responsibility or societal impact shape these changes? *P: Ethical guardrails; patient trust; transparency requirements; design constraints.* *Notes: RBMI effects on BM architecture.*
18.	Can you recall situations where AI required rethinking elements of the business model? *P: Revenue models; patient pathways; service integration; support structures.* *Notes: Complementarity, architectural change.*
Closing	
19.	Is there anything important about AI, innovation, or responsibility that we have not discussed? *P: Additional examples; overlooked elements.* *Notes: Capture emergent insights.*
20.	May I contact you for clarification during analysis? *P: Preferred contact method.* *Notes: Member-checking; dependability.*

Appendix D - Interview Summaries

Interview 1: AI in Daily Urology Practice

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee has been a physician (urology) for about four years and uses AI, particularly ChatGPT, for faster research in everyday clinical work. Additionally, the Interviewee is involved in a not-yet-founded AI startup based in a university live tech lab focusing on partially automating tumor board decisions. The goal is to support interdisciplinary clinical decisions in tumor boards while ensuring EU-compliant data protection.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	AI is currently seen as a major trend in medicine, motivating experimentation and adoption. Colleagues founding an AI startup and working toward habilitation highlight that AI enables fast-paced research with simple study designs that are easy to publish. This combination of visibility, momentum, and research opportunity acts as a primary driver.
3	What external influences shape how AI is explored or adopted?	Limited time and lack of regulatory capacity in medical employers shape how AI is used. Clinicians sometimes paste anonymized diagnosis lists into ChatGPT, comparing outputs with medical knowledge; AI is said to reach around "80% accuracy." Data protection is emphasized as essential.
4	What internal conditions or capabilities affect how AI is approached?	The organization invests few resources into AI for everyday physician work; time scarcity is a central internal barrier. As a result, physicians must proactively integrate AI tools themselves rather than following a structured organizational strategy. AI adoption is thus bottom-up driven.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	The Interviewee reports that there are no organizational guidelines for managing tensions between innovation and compliance/ethics. Consequently, there is no specific or formalized approach to such situations.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	No clear evidence. (Responsibility and ethics are only implied indirectly, mostly in relation to data protection and the assumption that systems are compliant. The closest reference comes from Q10, where the Interviewee states that there is no time to consider ethical issues.)
7	How are potential impacts explored before implementing AI-related changes?	No clear evidence. The Interviewee does not describe structured pre-implementation impact assessments. The only indirect reference is that clinicians test free LLMs with guideline-based scenarios, but without formalized evaluation.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection occurs informally through collegial exchange. Initial AI adoption emerged when a Venezuelan colleague used AI for translation, gradually normalizing its use. ChatGPT provides quick answers to complex questions, with sources checked afterwards ("open evidence"), representing a loose retrospective validation loop.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	No clear evidence. (The Interviewee does not identify formal stakeholder involvement. Decisions appear to be made predominantly by physicians, but this is not described as a participatory process.)
10	Can you describe how ethical or societal considerations influence daily work with AI?	According to the Interviewee, there are no ethical concerns in daily AI use, mainly because time constraints prevent deeper engagement with such topics. Data protection conformity is generally assumed. Physicians rely on their expertise and maintain decision authority, viewing AI primarily as supportive knowledge rather than decision-making automation.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Decision-making is individualized and case-specific: each patient is treated as a unique case. AI serves mainly for idea generation and narrowing research scope in diagnosis or document review, but final decisions are always made by physicians. No automated or AI-based decisions occur.
12	What structures, roles, or processes support oversight of AI?	The Interviewee states that no structures, roles or processes exist to oversee AI activities. There is no formal governance or supervision in place.
13	How do you assess, document, or monitor potential issues with AI systems over time?	According to the Interviewee, there are no established processes for evaluating, documenting or monitoring issues related to AI. No lifecycle governance mechanisms are in place.
14	When difficult decisions arise, how are they handled?	Difficult decisions are ultimately made by humans, especially physicians. For presentations, AI-generated drafts (e.g., via cloud tools) are used as templates, but sources are subsequently checked and content revised. Critical decisions with implications for specialist qualifications are always made without AI; AI is used only in rare diagnostic edge cases.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI shortens research workflows by providing targeted answers to specific questions, leading more quickly to relevant studies and papers. This enhances efficiency in knowledge work without fundamentally changing medical services. Value creation appears in streamlined information retrieval.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	AI is primarily used to present complex issues in a clear and structured way, thus enabling faster comprehension. Based on this, doctors can make more informed decisions, as the AI considers all aspects of the input, freeing up the doctor's time to research relevant specialist sources. Therefore, AI leads to faster and higher-quality decisions, although this is a perceived effect rather than a hard-measured, proven fact. . It is also used by foreign physicians for translation and understanding patient documentation. This reduces language barriers and accelerates clinical and research tasks. A Venezuelan colleague is cited as an example of such use.
17	How do considerations of responsibility or societal impact shape these changes?	The Interviewee notes that there is hardly any time in clinical work to consider responsibility or societal implications. AI is used "with some caution," but without deeper reflection. Responsibility remains primarily embedded in physician decision-making rather than formal processes.
18	Can you recall situations where AI required rethinking elements of the business model?	The Interviewee refers to a tool such as Microsoft 365 Copilot, designed to use internal company data for productivity gains. They suggest that such an integrated tool would ease daily work. However, the example is hypothetical, and no concrete business model changes are described.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	The Interviewee highlights the importance of legal aspects (e.g., the EU AI Act) and notes that many free LLMs are tested against guidelines and regulations. They emphasize that underlying studies are highly complex and often exceed what AI can capture, reinforcing that AI remains a "black box". Regarding data protection, the interviewee expresses the general view that misconduct with data never actually becomes apparent, since AI does not report violations on its own.
20	May I contact you for clarification during analysis?	The Interviewee agrees to be contacted for clarification and prefers email as the communication channel.

Interview 2: MedTech Expert on Responsible AI in Surgery

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee has 30+ years of global MedTech leadership experience, including building startups, leading robotics divisions, and advising multiple ventures. His work positions him at a strategic level observing AI's impact across major segments of healthcare, including robotics, diagnostics, and consumer health. He speaks from a high-level industry perspective rather than a single organization.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	He frames AI adoption as driven by hype cycles ("today's fancy word"), industry excitement, and investor expectations. Hospitals and companies often adopt AI to appear innovative, not because of structured strategic assessment. He notes AI is frequently introduced top-down without understanding user needs.
3	What external influences shape how AI is explored or adopted?	External factors include regulatory expectations (especially differences between EU, US, China), consumer law, and the global AI policy landscape. He explains Europe faces a dual regulatory burden (medical device regulation + EU AI Act), while countries like China adopt AI rapidly with fewer constraints. Consumer protection law also governs liability for defective AI-enabled devices.
4	What internal conditions or capabilities affect how AI is approached?	He describes poor alignment between hospitals, management, clinicians, and industry. Internal weaknesses include lack of consultation, insufficient training, missing governance structures, and absence of feedback loops. AI is often deployed without preparing users or aligning goals.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	He explains that historically, new technologies undergo a "gold rush → tragedy → governance" pattern. Ethical and regulatory considerations are often addressed only after incidents occur. AI is no exception: governance structures lag behind rapid innovation.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Ethical discussion is framed around patient safety, caregiver acceptance, and regulatory categories of sensitivity (data, staff info, device actions). He emphasizes differentiating types of sensitive information (patient data vs. staff images vs. device-critical data). Responsible AI requires structured consultation with users and patients.
7	How are potential impacts explored before implementing AI-related changes?	He suggests impacts are often not properly explored due to rushed implementation and hype. Companies and hospitals fail to consult end-users, leading to misaligned deployments and resistance. Only a few companies (e.g., Intuitive) conduct deep user consultations before rollout.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Teams often lack structured reflection loops; surgeons may distrust AI due to lack of transparency. Real-world unintended consequences include AI misinterpreting unfamiliar objects in imaging (e.g., radiopaque button mistaken for a tumor). He views retrospective human review as essential ("second set of eyes").
9	How are different groups or stakeholders involved in shaping AI-related decisions?	According to him, stakeholder involvement is generally inadequate: industry → hospitals → users → patients rarely consult each other effectively. He argues a structured consultation framework is essential to align priorities. Some companies invest deeply in multi-stakeholder consultation (e.g., Intuitive).
10	Can you describe how ethical or societal considerations influence daily work with AI?	Clinicians worry about trust, transparency, and being replaced. Ethical issues arise when AI suggestions cannot be explained ("black box"), reinforcing need for human-in-the-loop systems. Societal considerations also include patient comfort with AI involvement.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	He describes sector-wide governance gaps: AI deployment is often top-down, misaligned with clinical needs. Good practice requires user consultation, iterative introduction, and alignment across industry-hospital-clinician-patient levels.
12	What structures, roles, or processes support oversight of AI?	He states that governance structures are typically missing or informal; historically these only emerge after problems or adverse events. Oversight often lags behind implementation.
13	How do you assess, document, or monitor potential issues with AI systems over time?	He provides no description of monitoring processes; instead he emphasizes industry-wide failure to evaluate AI impacts, generate evidence, or collect longitudinal performance data. Many companies cannot demonstrate measurable value of AI tools.
14	When difficult decisions arise, how are they handled?	Difficult decisions often involve balancing AI suggestions vs. clinician judgment. His examples highlight the need for expert override in ambiguous or wrong AI outputs (e.g., misclassified imaging anomalies). He advocates augmentation rather than replacement.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI's strongest near-term value is reducing administrative burden and enhancing decision focus by surfacing relevant literature or narrowing data. He emphasizes AI's ability to reduce error rates and improve workflow efficiency.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	He describes emerging cloud-based ecosystems (e.g., Polyphonic, CareSyntax, Intuitive) aimed at capturing surgical knowledge and distributing insights. These systems reshape workflows by aggregating and rating insights. AI also amplifies need for cross-stakeholder collaboration.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility requires ensuring both patients and caregivers feel safe and informed. Ethical implementation involves building systems that enhance—not replace—clinical judgment. Societal impact also relates to future demographic shifts (e.g., baby boomer shortages), making responsible automation increasingly critical.
18	Can you recall situations where AI required rethinking elements of the business model?	He cites emerging business models around cloud-based knowledge aggregation and insight surfacing (e.g., rating systems). However, he highlights commercialization challenges because clinicians often won't pay for insights they feel they already possess. Value capture remains unresolved.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He highlights future demographic crises (e.g., 2030s caregiver shortages) and argues AI will become mandatory to maintain healthcare quality. He emphasizes intergenerational ethical obligations and long-term planning beyond current budget cycles.
20	May I contact you for clarification during analysis?	Yes. The Interviewee explicitly confirms the interviewer may reach out and expresses openness to further discussion.

Interview 3: AI Adoption Expert on Responsible Healthcare Innovation

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee describes himself as a "bridge builder" between technology and practice, entering the field through consulting and early involvement in a startup focused on digital anamnesis and discharge documentation. He currently serves as CEO of Company A, responsible for strategic direction, market development, and aligning the business portfolio to market needs. His work centers on connecting clinical practice pain points with technological solutions such as AI-assisted documentation.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	In the 2017 startup context, adoption was driven by clinical pressures such as demographic change, physician shortages, and inefficiencies in repetitive tasks like documentation. A physician founder envisioned AI-supported anamnesis to reduce system strain and improve documentation quality. Additional motivations included reducing error risk and supporting clinicians under high workload, including foreign-trained doctors still learning the language.
3	What external influences shape how AI is explored or adopted?	Externally, market pressures push organizations toward fast ROI, often leading to tool-first rather than business-case-first approaches. Regulatory frameworks in healthcare, including data protection (GDPR) and medical device regulations, significantly constrain adoption. He notes widespread fear, uncertainty, and misunderstandings among staff about data usage and model behavior.
4	What internal conditions or capabilities affect how AI is approached?	Internal success depends strongly on leadership mindset, organizational culture, error tolerance, and continuous competency development. Many leaders lack familiarity with collaborative experimentation and co-creation, which inhibits effective AI adoption. A supportive community within an organization can help reduce fear and build digital/AI readiness.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	The Interviewee shares a recent example of a medical practice selecting a low-cost check-in solution without considering GDPR and other regulatory requirements. He highlights the client's limited awareness of compliance risks and the tension between cost pressure and legal obligations. Ethical/compliance considerations were poorly integrated into the decision process.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	He emphasizes the need for transparency, training, and understanding of how AI systems work to avoid fear and misuse. Responsibility includes acknowledging data sensitivity and training heterogeneous development teams to reduce biases. Ethical concerns often arise when users lack clarity about model behavior or data flows.
7	How are potential impacts explored before implementing AI-related changes?	He notes that organizations frequently skip scenario analysis and risk identification due to lack of time, knowledge, or structured processes. Decisions are often made without adequate understanding of implications, leading to misaligned or unsafe AI implementations. He recommends maturity assessments to diagnose readiness before starting projects.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection varies widely: some teams rush due to time pressure, others recognize the value of asking stakeholders early. Many organizations lack structured reflection mechanisms, resulting in insufficient learning across teams. Employees sometimes proceed despite doubts, due to perceived pressure from leadership.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Stakeholder inclusion is inconsistent: some organizations recognize the need to involve staff, patients, UX designers, and developers early, while others skip engagement due to time constraints. Mature organizations assemble cross-functional teams including change managers, UX experts, developers, and clinical staff. Leadership involvement is critical for commitment.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical considerations mainly manifest as concerns about data security, "shadow AI" usage, and trustworthiness of outputs. Clinicians regularly bypass official systems due to workload, using tools like ChatGPT to find literature or ideas—raising ethical and security issues. Societal expectations around privacy and trust directly influence which tools are acceptable in healthcare.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Effective decision-making emerges through co-creation during the first AI project, integrating lessons into governance frameworks. He discourages creating governance entirely before practice-based learning occurs. Decision rules should evolve dynamically rather than be static documents.
12	What structures, roles, or processes support oversight of AI?	Oversight increasingly involves monitoring tools that detect compliance, shadow IT, and inappropriate tool use. He describes vendors offering "layered" monitoring systems that read from infrastructure to check conformity. Internal governance documents should also define responsibilities and permissible tools.
13	How do you assess, document, or monitor potential issues with AI systems over time?	The Interviewee describes monitoring emerging through infrastructure-level analytics detecting non-compliant or unauthorized AI usage. Many organizations lack mature documentation practices, leading to unmanaged risks. No systematic lifecycle documentation process is described for Company A.
14	When difficult decisions arise, how are they handled?	Difficult AI decisions are often shaped by organizational readiness and the capability of staff to challenge leadership decisions. He notes many decision-makers lack foundational knowledge, leading to suboptimal or risky choices. He recommends readiness assessments to support evidence-based decision-making.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI strongly impacts pharmaceutical R&D (drug discovery) by compressing multi-year data analysis into weeks. In clinical settings, radiology and other diagnostic processes gain efficiency through improved image triage and human-in-the-loop review. Administrative efficiency and documentation enhancement also contribute to value delivery.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	Workflows increasingly integrate AI-supported documentation, automated transcription, and background intelligence to reduce manual effort. Partnerships expand toward infrastructure providers enabling secure speech-to-text, automated coding, and governance-compatible tools. AI frees clinicians to focus more on patient care rather than administrative tasks.
17	How do considerations of responsibility or societal impact shape these changes?	Societal pressures such as demographic change, workforce shortages, and shrinking hospital networks drive responsible adoption. AI is seen as a necessary tool to maintain quality of care amid declining staff availability. Responsibility also includes ensuring clinicians spend time on meaningful tasks rather than administrative burdens.
18	Can you recall situations where AI required rethinking elements of the business model?	The Interviewee does not give a specific example of business model transformation but notes growing demand for tools automating speech, documentation, and process management. He describes contexts where AI becomes necessary due to workload or demographic pressures, implying indirect business model adaptations.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He stresses the importance of heterogeneous development teams to mitigate bias, improve software outcomes, and maintain user trust. A key risk is that erroneous AI outputs may lead to generalized distrust unless teams are well-trained and systems transparent. AI literacy and societal education are essential for responsible adoption.
20	May I contact you for clarification during analysis?	Yes. The Interviewee expresses openness to continued exchange, including follow-up conversations and receiving the Executive Summary once the thesis is complete.

Interview 4: Cardiologist on AI-Enabled Diagnostics

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a cardiologist/angiologist in specialty training with frequent diagnostic responsibilities, including emergency EKG interpretation and inpatient care. His main AI touchpoints are a cardiology EKG interpretation app and an evidence-retrieval tool for medical literature. These tools support clinical decisions and keep him current on fast-evolving medical knowledge.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	AI adoption emerged from clinician demand rather than organizational strategy. Colleagues discovered effective tools informally at conferences and introduced them to peers. Motivation was driven by performance advantages, with the EKG model outperforming senior clinicians in identifying subtle infarct signs.
3	What external influences shape how AI is explored or adopted?	External influences include app availability, international research networks, and data quality from large annotated datasets. Concerns also include vendor geography and perceived data security risks, such as skepticism toward a tool hosted in Eastern Europe. Market supply of free/paid versions also shapes use.
4	What internal conditions or capabilities affect how AI is approached?	There is no structured introduction of AI at Company A; uptake is dominated by residents and younger clinicians who self-educate. Leadership is described as skeptical and not digitally oriented, limiting top-down support. Informal peer networks substitute for formal capability-building.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	The organization does not provide explicit guidance on compliance, governance, or ethical handling of AI. Residents often rely on private devices due to lack of employer licensing, creating shadow-AI use. Ethical questions are managed informally, with responsibility retained by clinicians.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Responsibility remains entirely with clinicians. Output from AI tools is reviewed critically, and decisions are adjusted based on contextual factors not captured by models. Formal training is either misaligned or impractical, as official courses prohibit the very tools being used.
7	How are potential impacts explored before implementing AI-related changes?	No structured impact assessment is conducted. Use occurs informally and autonomously by clinicians, who review original literature and evaluate plausibility case-by-case. Training or approval processes are not adapted to actual practices.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection is informal and case-based, typically through discussion among residents and with senior physicians. Clinicians adjust AI-informed decisions based on broader clinical factors and personal judgment. There is no routine structured reflection loop.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Stakeholder involvement is minimal. Adoption is peer-driven among residents, occasionally supported by more open-minded senior staff. Patients are not involved in tool selection; leadership provides no input beyond skepticism.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical considerations include the need to confirm AI recommendations manually and avoid overreliance. AI use is not disclosed to patients in most cases, as clinicians seek confirmation rather than delegation. Societal aspects appear indirectly when patients independently use generative AI for self-information.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	There is no formal decision-making structure for AI use. Each clinician independently decides whether and how to use AI tools. Decisions rely on medical judgment and senior consultation rather than AI-specific governance.
12	What structures, roles, or processes support oversight of AI?	No oversight structures exist. Shadow-AI use via private devices occurs without monitoring, documentation, or institutional controls. Only one officially approved AI tool (thorax X-ray assistant) is institutionally deployed and flagged as "for review".
13	How do you assess, document, or monitor potential issues with AI systems over time?	There is no documentation or monitoring of AI usage or performance. Clinicians validate AI suggestions through personal expertise and literature review but do not record AI involvement in decisions.
14	When difficult decisions arise, how are they handled?	Difficult decisions are resolved through human judgment and discussion with colleagues. AI serves only as an input for idea generation and never as a determinant in high-stakes clinical choices. Human consultation supersedes algorithmic output.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI influences clinical efficiency by providing faster literature access and potentially higher diagnostic precision. In diagnostics like EKG and thoracic imaging, AI enhances quality of assessment but does not currently change workflow ownership or official policy. Value creation occurs at the level of improved decision orientation rather than organizational service transformation.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	Workflows are moderately affected: clinicians use AI for diagnostic support and literature triage, while official radiology tools add automated assessments to reports. Roles and partnerships remain unchanged, as AI is introduced informally rather than through structured programs.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility demands that AI is used only as supportive input, not as a replacement for clinical decision-making. Societal effects include patient self-education through generative AI, which sometimes produces accurate insights. Clinicians remain cautious and emphasize that accountability remains entirely human.
18	Can you recall situations where AI required rethinking elements of the business model?	No clear evidence. The Interviewee describes future use potential (e.g., catheter imaging interpretation, stent recommendation systems) but does not indicate any organizational business model changes.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	The Interviewee highlights overlooked stakeholder perspectives, especially patients' independent use of generative AI. He notes that patient-generated AI insights can be accurate and influence clinical dialogue. This underscores the need to consider multi-sided AI ecosystems in healthcare.
20	May I contact you for clarification during analysis?	Yes. The Interviewee explicitly welcomes follow-up contact and expresses interest in reading the study's results.

Interview 5: Neurology Clinician on AI in Everyday Practice

#	Guide Question (verbatim)	Summarized Answer (2-4 sentences)
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a practicing physician in neurology working in an acute hospital setting. She uses an AI-supported system ("Apennio") introduced by the employer for medication safety, documentation, and workflow support. Her daily work interacts with AI for medication checks, contraindications, and digital documentation.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	The AI system was introduced as part of a hospital-wide digitalization effort and cost-saving measure, particularly replacing paper records and improving documentation processes. The Interviewee reports no involvement in selection; it was imposed top-down. Drivers were cost, documentation requirements, and digital record-keeping.
3	What external influences shape how AI is explored or adopted?	External influences include regulatory demands for proper medication documentation and error traceability. The system supports legally required documentation and safety tracking. Additionally, IT and data protection constraints limit AI expansion.
4	What internal conditions or capabilities affect how AI is approached?	Internal capabilities vary widely: younger colleagues adopt AI more easily, while older clinicians struggle with prompts and navigation. Training was inconsistent, and onboarding new staff depends heavily on peer teaching. Time pressure limits structured learning.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	Top-down introduction resulted in limited ethical preparedness. A major incident occurred when a patient letter revealed AI involvement, causing dissatisfaction among patients, leadership, and data protection officers. The organization reacted by emphasizing caution but without formalized processes.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Ethical issues are managed reactively. Clinicians must clarify to patients that AI was used only for grammar or suggestions, not for processing personal data. Responsibility remains with the physician, and no formal ethical oversight exists.
7	How are potential impacts explored before implementing AI-related changes?	No systematic pre-assessment took place. The system was introduced with minimal consultation or foresight. Operational issues surfaced only after use, and fixes are sent to the vendor ad hoc.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection happens informally and only when problems arise. Time scarcity prevents structured reviews. Issues are collected through the Interviewee's role as a representative for assistants and forwarded via email to responsible staff.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Stakeholder involvement is minimal; the tool was chosen by management without clinical input. Two designated staff (one medical, one nursing) act as liaisons for problem management but do not serve as ethical or strategic oversight bodies. No patient or multidisciplinary stakeholder engagement occurs.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical considerations arise primarily in managing AI outputs that may misinform or cause patient concern. Human review is essential, as AI cannot interpret contextual factors like age in medication warnings. Clinicians avoid disclosing AI use unless necessary to prevent patient distrust.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Decision-making is entirely top-down. Clinicians received the system after management decided to adopt it. Ongoing decisions about functionality and updates occur between liaison staff and the vendor.
12	What structures, roles, or processes support oversight of AI?	Oversight structures are minimal. Two liaison roles handle operational issues but do not evaluate ethics, safety, or compliance. No formal governance boards exist.
13	How do you assess, document, or monitor potential issues with AI systems over time?	Monitoring is reactive: clinicians report issues to the two-liaison staff, who escalate them to the vendor. There is no documentation system for tracking AI failures or decision impact. Frontline staff do not see how issues are resolved.
14	When difficult decisions arise, how are they handled?	Difficult decisions rely on clinical judgment rather than AI. If AI outputs appear implausible, staff escalate concerns to liaison roles rather than follow questionable recommendations. Human expertise overrides AI suggestions.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI improves medication safety, reduces lookup time, and enhances documentation reliability. However, its limited interoperability creates inefficiencies through manual copy-paste between systems. Value creation is operational, not strategic.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	Workflows changed in medication ordering and documentation, requiring new skills in prompting and system navigation. The hospital created dedicated liaison roles to manage AI-related issues. AI has not yet reduced workload meaningfully due to interoperability gaps.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility concerns manifest in reluctance to automate decisions, especially given AI's inability to contextualize patient factors. Societal concerns include patient discomfort when AI involvement becomes visible. These factors reinforce the need for human verification.
18	Can you recall situations where AI required rethinking elements of the business model?	No clear evidence. The Interviewee discusses desired AI applications for reducing documentation in emergency intake but does not describe any business model rethinking initiated by current AI use.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	She highlights concerns about the future of certain specialties, such as radiology, given AI's growing diagnostic capacity. She sees potential long-term workforce and career impacts. At the same time, she acknowledges that AI may be necessary to address workforce shortages.
20	May I contact you for clarification during analysis?	Yes. The Interviewee explicitly agrees and offers to help connect with additional relevant staff.

Interview 6: Health-IT CEO on Responsible Clinical AI

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is CEO of Company A, a software provider delivering medical documentation and administrative workflows for hospital staff. His work involves building digital solutions aimed at reducing administrative burden, improving data quality, and integrating AI capabilities into routine processes. He oversees strategic product development, customer-facing innovation, and partnerships.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	Adoption began due to clear customer pain points around clinical documentation, billing, and time pressure. Hospitals demanded automation to help compensate for staff shortages and rising administrative burden. Competitive pressure in the healthcare IT market also pushed experimentation with AI-based documentation support.
3	What external influences shape how AI is explored or adopted?	Regulatory expectations including data protection constraints shape what can be implemented. Market competition and customer expectations also exert pressure to build AI features. Vendor relationships and the rapid development cycles of large tech companies influence the ecosystem.
4	What internal conditions or capabilities affect how AI is approached?	Internal capabilities include a tech-proficient workforce and agile product development. The team must balance innovation with strict healthcare compliance requirements. Resource limitations and competing priorities influence how fast AI features can be deployed.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	Compliance always takes precedence over innovation. Legal review determines feasibility, and ethically questionable features are not pursued. The company prefers slower releases over regulatory risk.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Responsibility is addressed by ensuring AI never replaces clinical judgment and remains a supportive tool. Ethical considerations include avoiding hallucinations, ensuring transparent system behaviour, and communicating limitations to clinicians. The company is cautious with generative AI due to risk of incorrect content.
7	How are potential impacts explored before implementing AI-related changes?	Impact assessments occur through customer testing, pilot environments, and cross-functional review. The Interviewee emphasizes iterative validation and controlled rollout before full deployment. Potential risks such as misinformation, workflow disruption, or trust issues are evaluated early.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Teams reflect through regular internal assessments, customer feedback loops, and retrospective discussions after pilots. Unexpected issues like misinterpretations or user confusion trigger immediate review. Learning loops are embedded in the agile development process.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Clinicians, nurses, and hospital administrators are actively involved in shaping requirements and testing prototypes. Feedback from diverse professional groups informs design and functionality. External experts and partners are also brought in for specialized perspectives.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical concerns influence design choices such as maintaining human oversight, preventing over-automation, and ensuring traceability. Societal expectations around safety and transparency shape communication with customers. The organization avoids features that could undermine patient trust.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Decision-making is centralized but consultative: leadership sets direction, while product teams and subject-matter experts contribute analysis. Customer needs influence prioritization. Compliance and legal teams have veto authority for risky features.
12	What structures, roles, or processes support oversight of AI?	Oversight is provided by internal compliance/legal review, structured product governance, and clear process checkpoints. Cross-functional meetings ensure that AI-related risks are monitored. Certain roles specialize in data protection and risk assessment.
13	How do you assess, document, or monitor potential issues with AI systems over time?	Issues are documented through internal ticketing, customer support channels, and monitoring tools. Continuous updates and quality assurance ensure long-term stability. Feedback from clinicians informs the tracking of model behaviour over time.
14	When difficult decisions arise, how are they handled?	Difficult decisions involve cross-functional dialogue and risk-weighted analysis. The Interviewee prioritizes patient safety and regulatory compliance over commercial advantage. If uncertainty remains, the company postpones release.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI enhances value by improving documentation efficiency, reducing administrative burden, and helping clinicians focus on patient care. It enables new feature categories such as structured summarization and automated insights. The Interviewee sees AI as central to future competitiveness.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	Workflows increasingly integrate AI-assisted documentation and structured inputs. Clinicians require new digital skills, while the company forms partnerships with AI vendors and data specialists. Roles evolve to include oversight of automated components.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility influences the decision to avoid full automation and ensure human review. Societal concerns about accuracy and trustworthiness limit which AI tasks are delegated. These constraints shape feature design and business positioning.
18	Can you recall situations where AI required rethinking elements of the business model?	The Interviewee notes that AI opens potential new revenue streams and service offerings, but the company is cautious. There is acknowledgment that AI may reshape pricing models or support contracts, though no concrete redesign has yet occurred.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He emphasizes the need for realistic expectations and avoidance of AI hype, especially among small and medium-sized healthcare providers. He warns against misunderstandings of AI capabilities and stresses clear communication.
20	May I contact you for clarification during analysis?	Yes, the Interviewee explicitly agrees and remains open to follow-up communication.

Interview 7: Frontline Educator's Perspective on AI in Nursing Education

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is an educator and program lead for intensive and anesthesia nursing training at a hospital-based school. She previously worked in intensive care and now designs and delivers curricula for advanced nursing education. Her role involves integrating digital tools into training and tracking emerging AI/robotics developments relevant to nursing practice.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	Adoption is driven by increasing care complexity, demographic change, and staff overload in nursing. AI is seen as necessary to relieve physical and cognitive burden and to prevent illness and burnout among caregivers. She expects that without AI, the care system will be unable to function sustainably.
3	What external influences shape how AI is explored or adopted?	Regulatory uncertainty and missing legal frameworks strongly shape adoption. She emphasizes that current law provides hardly any guidance on AI in practice. External communication requirements also matter, such as informing patients and the public when robotics or AI are used.
4	What internal conditions or capabilities affect how AI is approached?	Internal readiness is low, especially among long-serving staff with little digital experience. Training must start "from scratch," covering basic digital skills, robotics and AI concepts. Planned curriculum updates face capacity and expertise constraints on the educator side.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	She notes that ethical frameworks and legislation lag far behind technological developments. While data protection is addressed more systematically, ethical principles for AI are largely missing. As a result, ethical handling is underdeveloped and often reactive rather than embedded.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Ethics is recognized as important and appears in teaching, but is not consistently operationalized in practice. AI-specific ethics remains more of a discussed aspiration than a structured practice. Responsibility often rests with individual educators rather than a formal body.
7	How are potential impacts explored before implementing AI-related changes?	No clear evidence of structured foresight or scenario analysis. She mainly notes that much AI and robotics work remains at university or research level and has not reached everyday practice.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection occurs informally through conversations with learners and colleagues. Many participants express fear and uncertainty about using technology correctly, which is then addressed through didactic adjustments. There is no standardized reflection routine.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Quality Management (QM), external experts and curriculum partners are involved especially regarding patient information and external communication. These stakeholders influence how AI/robotics is presented and explained, but do not constitute a formal AI governance forum.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical considerations focus on transparency and preventing harm, especially in relation to robotics at the bedside. She stresses that all ethical aspects must be considered so that patients are not frightened or harmed by technology use. This leads to careful planning of information and implementation steps.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Decision-making is largely top-down: ministries and legal frameworks define curricula and requirements, which the school must then implement. The educational unit has some autonomy in didactic design, but not in whether to address digital/AI topics.
12	What structures, roles, or processes support oversight of AI?	Oversight is primarily carried out through Quality Management structures rather than AI-specific governance bodies. QM monitors patient information materials and external communication on technology use. There are no dedicated AI oversight roles.
13	How do you assess, document, or monitor potential issues with AI systems over time?	Monitoring occurs indirectly through QM feedback loops and integration into curriculum updates. Issues or concerns arising in practice or training are to be taken up and reflected in future teaching. There is no dedicated AI incident reporting or tracking system.
14	When difficult decisions arise, how are they handled?	At present, difficult decisions are handled by individuals drawing on their expertise; there are no formalized decision bodies for AI-related dilemmas. She suggests that coaching and structured working groups would be desirable to support such decisions but are not yet implemented.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI and robotics are perceived as having high potential to support nursing by reducing physical strain, enabling patient-technology communication, and optimizing workflows. She mentions tools such as smart beds and integrated communication systems as examples of value-creating innovations. However, she notes that many of these applications are still slow to reach everyday care.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	Workflows are beginning to shift through the integration of robotics and AI-supported educational tools (e.g., assessment systems). Nurses and educators need new competencies to understand and guide these technologies. Partnerships with external experts are important to bring in diverse perspectives and specialist knowledge for curriculum development.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility and societal impact are framed primarily through the need to prevent collapse of the care system under demographic pressure. AI is seen as necessary to relieve staff and maintain humane care standards. The goal is explicitly to support, not replace, human caregivers.
18	Can you recall situations where AI required rethinking elements of the business model?	No clear evidence of business model rethinking. She discusses system-level challenges and workforce relief, but does not describe specific organizational business model changes triggered by AI.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	She emphasizes the importance of relationship-focused didactics and building trust when introducing AI and robotics. Her key message is that technology should serve to improve care at the bedside and preserve human relationships, not undermine them.
20	May I contact you for clarification during analysis?	Yes. The Interviewee agrees to follow-up contact and even invites further collaboration and mutual visits for exchange.

Interview 8: Radiologist on AI in Everyday Imaging

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a radiologist with 15 years of experience as a practice owner, now employed. He oversees radiological diagnostics and interacts with emerging digital imaging technologies. AI-supported tools intersect with his daily work in image interpretation.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	AI is considered because of rising workload and the need for diagnostic efficiency and precision. Existing tools serve as add-ons to support tasks such as mammography second readings or angle measurements. Cost continues to be a barrier to broader adoption.
3	What external influences shape how AI is explored or adopted?	Strict German regulations constrain AI's diagnostic use, allowing it only as a "third reader." Lack of insurer reimbursement discourages implementation, as many tools would require patients to pay privately. Market availability exists, but economic viability is low.
4	What internal conditions or capabilities affect how AI is approached?	Internal adoption depends on price and reimbursement structure. Radiologists value AI's potential added safety but lack financial incentive to pay per-case fees.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	Human oversight is non-negotiable; AI cannot be used without clinician supervision. Ethical comfort depends on maintaining control and verifying plausibility.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	He views it as ethically wrong to withhold effective AI when evidence shows Mensch+AI performs best. Human review is still required, preserving responsibility.
7	How are potential impacts explored before implementing AI-related changes?	No structured process is mentioned. Evaluation is based mainly on available studies and peer experience.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection is informal: he tests AI tools privately on anonymized images and compares results with clinical reasoning. These experiments reveal both strengths and limitations.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Decisions occur internally among colleagues. Broader stakeholder involvement is absent.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical practice emphasizes human oversight, especially because AI may miss rare findings. Concern focuses on avoiding blind trust in automated suggestions.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Decision-making relies on internal discussions and practical cost-benefit considerations. Final responsibility stays with clinicians, not with AI tools.
12	What structures, roles, or processes support oversight of AI?	Oversight is minimal; AI is typically embedded in vendor software. Updates and performance depend largely on manufacturer processes.
13	How do you assess, document, or monitor potential issues with AI systems over time?	No monitoring structures are described. Issues would be noticed in everyday work, but no formal reporting exists.
14	When difficult decisions arise, how are they handled?	Difficult diagnostic decisions rely on human expertise; AI may highlight findings, but the clinician determines relevance. Rare or unusual findings particularly require human evaluation.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI embedded in scanners enhances image quality, reduces radiation doses, and shortens scan times. This improves throughput and clinical efficiency.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	AI shows potential to reduce workload through pre-measured data and support for differential diagnosis. However, many tasks (e.g., staging) remain manual, limiting large-scale workflow transformation.
17	How do considerations of responsibility or societal impact shape these changes?	Societal responsibility requires human oversight, especially for rare conditions AI is not trained on. Clinicians remain accountable to avoid misdiagnosis.
18	Can you recall situations where AI required rethinking elements of the business model?	No major business model changes documented. He mentions potential automation of telephone and scheduling tasks but no actual implementation.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He emphasizes optimism about future diagnostic advances driven by AI. He expects technology to increasingly support clinicians.
20	May I contact you for clarification during analysis?	Yes, he agrees and expresses interest in the thesis outcome.

Interview 9: Physician-Executive on Responsible AI in Healthcare

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a physician with 15 years of clinical experience who transitioned into MedTech entrepreneurship. His work is deeply connected to AI, particularly in NLP-based clinical data analysis. He has built companies across digital health, medical devices, and AI-enabled platforms.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	A pivotal experience occurred when he saw an NLP system derive clinical insights faster than humans, convincing him of AI's transformative potential. This event drove him to leave frontline care and build AI-enabled systems.
3	What external influences shape how AI is explored or adopted?	Cross-border privacy laws, differing regulatory expectations, and jurisdictional constraints strongly influence adoption. The Interviewee highlights GDPR, US HIPAA/BAA frameworks, and UK practices as major external forces.
4	What internal conditions or capabilities affect how AI is approached?	Internal challenges include legal uncertainty, data ownership ambiguity, and technical issues such as versioning and data persistence. Emerging tech introduces complexity that organizations must navigate without established standards.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	Conflicts frequently emerged with sensitive patient data being processed by third parties. Compliance frameworks like BAAs were used to manage risk, but were insufficient outside the US. Regulatory friction was a constant barrier.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Responsibility centers on patient care impact. He prioritizes technologies that improve outcomes and acknowledges that early AI is experimental and not fully predictable. Ethical considerations are weighed alongside feasibility.
7	How are potential impacts explored before implementing AI-related changes?	No clear evidence of structured impact assessment. He describes emerging issues during development rather than proactive foresight.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Teams initially relied on human gold standards to validate outputs. As systems advanced, validation shifted to software-based standards, making oversight more complex. Model evolution introduced new risks in traceability.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Stakeholder involvement spans regulators, data controllers, patients, and third-party processors. However, no structured engagement process is described.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical boundaries are governed by patient-centric reasoning. Risks such as hallucinations require human judgment and cautious deployment.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Governance occurs at several layers: government, organizational leadership, and algorithmic self-governance. As models evolve, tracing decision processes becomes more difficult.
12	What structures, roles, or processes support oversight of AI?	Oversight depends largely on audits comparing outputs against gold standards. As systems evolve, oversight becomes increasingly challenging.
13	How do you assess, document, or monitor potential issues with AI systems over time?	Monitoring must be version-based rather than time-based. Each algorithm update requires renewed auditing to check for degradation or corruption.
14	When difficult decisions arise, how are they handled?	Decisions rely on legal adjudication and error analysis due to limited human interpretability of deep models. He anticipates future lawsuits to clarify liability.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI reduces labor in image and data processing and shifts value creation toward automation and semantic understanding. Emerging AI capabilities will transform medical interpretation workflows.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	AI is expected to automate frontline cognitive tasks, enabling clinicians to focus on higher-level oversight. Partnerships will increasingly revolve around AI platforms, interoperability, and semantics.
17	How do considerations of responsibility or societal impact shape these changes?	Demographic and global access challenges drive the need for AI to scale clinical capacity. He sees AI as essential to supporting underserved populations.
18	Can you recall situations where AI required rethinking elements of the business model?	He describes a paradigm shift toward global scale via digital assistants. However, no specific business model pivot from his own companies is given.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He highlights that AI represents a new exponential paradigm similar to the early Internet. The healthcare system will be fundamentally reshaped.
20	May I contact you for clarification during analysis?	Yes, he explicitly agrees to follow-up.

Interview 10: Clinical Caution and Emerging AI Utility in Specialist Cardiology

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a specialist in internal medicine / cardiology working in an outpatient cardiology practice. In daily work, he uses a speech recognition program that converts dictated letters into text, but he is unsure whether this already counts as “AI.” He emphasizes that they do not use systems that passively record entire consultations.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	The Interviewee notes the existence of speech recognition and potential future uses, but he does not describe specific factors or events that drove the initial adoption decision.
3	What external influences shape how AI is explored or adopted?	The Interviewee explains that AI vendors already approach the practice with AI-based services (e.g. digital assistants / scheduling tools). He receives emails and letters about such offerings, but there is no intensive direct sales pressure such as frequent calls.
4	What internal conditions or capabilities affect how AI is approached?	The Interviewee does not see a benefit from AI-based ECG reporting in his routine work but considers it potentially useful in very complex cases (e.g. under chemotherapy). He also stresses that he does not currently see passive recording of consultations as appropriate for their practice. At the same time, he expects that staff shortages (e.g. not enough people to answer phones) will make AI-based assistants for organisational tasks increasingly necessary.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	The Interviewee expresses ethical and data-protection concerns but does not describe any concrete organisational procedures or decision rules for handling such conflicts.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	The Interviewee voices a strongly sceptical view on data security and ethical risks, arguing that any stored data can, in principle, be accessed by unauthorised actors. He therefore sees digitalisation and AI use as ethically sensitive but does not describe any formal mechanisms or committees. Instead, his contribution remains at the level of a normative warning.
7	How are potential impacts explored before implementing AI-related changes?	No clear evidence. The Interviewee does not report any structured assessments, simulations, or formal evaluations of impacts before adopting AI tools.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	No clear evidence. The Interviewee does not describe any explicit reflection routines, learning loops, or team-based reviews of assumptions and uncertainties regarding AI.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	The Interviewee mentions vendors and staff constraints but does not explain any structured involvement of patients, staff, partners, or other stakeholders in AI decision-making.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical and societal concerns influence the Interviewee’s stance by making him cautious about “abolishing” the medical profession through AI. He argues that physicians must critically reflect on their own work ethic and expectations (e.g. short working hours and high pay), as this may increase their replaceability. He also anticipates significant reductions in demand for radiologists due to AI in imaging, which he frames as problematic.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	The Interviewee comments on specific tools he does or does not see as useful, but does not describe how AI-related decisions are structured or by whom they are formally taken.
12	What structures, roles, or processes support oversight of AI?	No clear evidence. The Interviewee does not mention any oversight roles, committees, or monitoring processes for AI within the organisation.
13	How do you assess, document, or monitor potential issues with AI systems over time?	No clear evidence. There is no description of audits, documentation standards, or long-term monitoring of AI performance.
14	When difficult decisions arise, how are they handled?	No clear evidence. The Interviewee does not describe specific decision processes or escalation pathways for difficult trade-offs involving AI.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	The Interviewee reports that speech recognition already streamlines documentation by converting dictated letters directly into text, thus making reporting more efficient. He also expects future AI-based ECG and ultrasound reporting to support more differentiated clinical questions, especially in complex cases, which would enhance diagnostic value. However, he states that in his current routine he does not yet see a tangible benefit from AI-generated ECG reports.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	The Interviewee anticipates that AI will substantially reshape diagnostic workflows, with most imaging and ultrasound reports eventually generated by AI and only selected findings reviewed by humans. He expects unremarkable chest X-rays to be reported without human inspection and predicts that radiology will experience a strong drop in demand for physicians. In organisational workflows, he believes AI-based assistants (e.g. for appointment management and telephone triage) will become necessary due to persistent staffing shortages.
17	How do considerations of responsibility or societal impact shape these changes?	The Interviewee links AI adoption to potential large-scale workforce effects, especially in radiology, and warns against unreflective self-replacement of physicians. He frames responsibility partly as a matter of professional self-understanding and willingness to work, suggesting that complacency can increase the risk of being replaced by AI. At the societal level, he is pessimistic about data security and fears that stored medical data will always be vulnerable to unauthorised access.
18	Can you recall situations where AI required rethinking elements of the business model?	No clear evidence. The Interviewee mentions possible future reliance on AI tools for appointment management and diagnostic reporting but does not describe any concrete changes in revenue models, service offerings, or partnerships in his own setting.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	In his broader reflections, the Interviewee underlines that AI will have a very large significance in medicine but must be handled carefully to avoid “abolishing” physicians. He highlights radiology as a field where demand for doctors is likely to fall sharply and calls for self-reflection among physicians about their contribution, work ethic, and expectations. Combined with his strong concerns about data security, his closing stance is both forward-looking and sceptical.
20	May I contact you for clarification during analysis?	No clear evidence. In the available transcript excerpts, the Interviewee does not explicitly address whether he agrees to be contacted again for clarification.

Interview 11: Ethical Caution and Efficiency Constraints in AI for Cardiology

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a cardiologist working in an outpatient practice. He states that the team currently has no direct contact with AI systems. He acknowledges that AI could potentially support long-term ECG and blood-pressure analysis in the future, but this is not implemented yet.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	No adoption of AI has taken place yet. The Interviewee emphasises that the practice is fully occupied, leaving no current need or pressure to integrate AI tools. Expansion to a new practice may create future interest.
3	What external influences shape how AI is explored or adopted?	External AI vendors do not directly contact him, but he identifies cost as the main external determinant influencing adoption decisions. Cost makes him hesitant to consider AI products at this stage.
4	What internal conditions or capabilities affect how AI is approached?	High workload and current efficiency of diagnostic processes reduce internal motivation to adopt AI. He notes their structured reporting workflow is already very fast, so AI brings no immediate gain. Opening a new practice with additional colleagues might shift this.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	No clear evidence. He does not describe any procedures or organisational routines for balancing innovation and compliance.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	The Interviewee expresses strong ethical concerns about data protection. He argues that hacking of digital medical data could have “gigantic” consequences, especially if insurers access sensitive health information. He highlights risks for credit, insurance, and livelihoods.
7	How are potential impacts explored before implementing AI-related changes?	No structured impact assessment appears to exist. His stance shows risk awareness, but no mention of formal evaluations or foresight mechanisms.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	No clear evidence of team-level reflection routines. He focuses mainly on security concerns and future technological impacts, not on organisational learning processes.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	No clear evidence. He does not describe involvement of staff, patients, partners, or external experts in AI-related decisions.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical concerns strongly shape his views. He emphasises that data breaches linked to AI/cloud systems could negatively affect insurance access and credit decisions. Daily skepticism stems from perceived vulnerability of digital patient data.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	No clear evidence. He does not explain who decides about AI adoption or what internal decision-making structures exist.
12	What structures, roles, or processes support oversight of AI?	No clear evidence. The Interviewee does not mention any oversight mechanisms or roles related to AI governance.
13	How do you assess, document, or monitor potential issues with AI systems over time?	No clear evidence. He briefly notes that AI could support filtering artefacts in ECGs but does not describe monitoring or documentation procedures.
14	When difficult decisions arise, how are they handled?	No clear evidence. He does not provide examples of difficult decision-making processes around clinical, operational, or ethical AI dilemmas.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI is expected to enhance diagnostic efficiency by filtering artefacts from long-term ECGs and improving reporting speed. He anticipates future AI modules in ECG systems and sees potential value primarily in supporting diagnostic workflows.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	For the new practice, he plans to integrate several AI-based or AI-enhanced systems (e.g., new telephone system, operating system, EKG evaluation modules). These tools are expected to streamline organisation, reduce manual tasks, and support diagnosis.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility concerns focus on data risks and the societal implications of AI-driven automation. He warns that many diagnostic specialties may become replaceable, while procedural/manual fields may remain less affected.
18	Can you recall situations where AI required rethinking elements of the business model?	He describes how AI could enable direct-to-patient reporting (e.g., via smartphone notifications), reducing dependency on specialists. He also sees the general practitioner becoming the central coordinator due to AI-generated specialist-level reports.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He predicts that AI will revolutionise medical diagnostics, especially in radiology and dermatology, due to large training datasets that outperform subjective human judgment. While expecting major progress, he is unsure whether AI will live up to the hype.
20	May I contact you for clarification during analysis?	No clear evidence. The transcript ends without him addressing follow-up contact.

Interview 12: Physician Executive Leading Responsible AI Governance

In this case, the questions were answered in writing. For the sake of readability and consistency, the summary is presented in the same way as in all other interviews.

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a board-certified urologist and the Founder & Executive Lead of an international non-profit initiative focused on physician-led medical AI. His role spans strategic oversight, governance design, and clinical quality assurance across international pilot sites. The work is explicitly centered on responsible and clinically grounded AI innovation.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	AI adoption was driven by structural clinical challenges, rising complexity, and resource constraints. A lack of clinically grounded AI solutions and growing regulatory pressure further accelerated engagement. Global interest in responsible AI acted as an additional catalyst.
3	What external influences shape how AI is explored or adopted?	External influences include European regulation, data protection requirements, and accreditation standards. International partner expectations and global trends toward Responsible AI further shape how AI is explored and implemented.
4	What internal conditions or capabilities affect how AI is approached?	Internally, AI adoption is enabled by clinical leadership, digital maturity, and interdisciplinary teams. A strong safety culture and international pilot hubs support structured experimentation and validation. These capabilities allow systematic rather than ad-hoc AI use.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	Patient safety and regulatory compliance take priority over innovation speed. Conflicts are addressed through cross-functional evaluation, and projects may be paused if risks remain unclear. This indicates a precautionary decision logic.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Ethical, clinical, and societal risks are addressed early in AI projects. Physicians and technical teams jointly evaluate implications and formally document decisions. Responsibility is treated as an integrated design concern rather than an afterthought.
7	How are potential impacts explored before implementing AI-related changes?	The organization uses structured impact assessments before implementation. This includes scenario testing, risk identification, stakeholder mapping, and early validation in pilot hubs. These practices aim to anticipate downstream effects.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection is embedded throughout the AI lifecycle. Defined reflection points occur before development, during iteration, and before and after deployment. This supports continuous learning and adjustment.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	A broad range of stakeholders is involved, including clinicians, nurses, patients, technical teams, governance bodies, and international partners. These groups actively contribute to decision-shaping processes.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical considerations shape transparency, explainability, and guardrails in daily AI work. Continuous monitoring influences both design and operational decisions. Ethical principles are embedded into routine practice.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	AI decision-making follows a three-layer governance model. Clinical leadership, technical governance, and executive steering jointly shape decisions. This structure separates responsibilities while maintaining oversight.
12	What structures, roles, or processes support oversight of AI?	Oversight is supported by formal bodies and roles, including a Clinical & Scientific Board, model owners, and working groups. Pilot site structures further contribute to governance maturity.
13	How do you assess, document, or monitor potential issues with AI systems over time?	The organization relies on lifecycle documentation, audits, and drift monitoring. Clinical validation and automated risk triggers are used to identify emerging issues. Monitoring is continuous rather than episodic.
14	When difficult decisions arise, how are they handled?	Difficult decisions follow defined escalation principles. Clinical safety, regulatory compliance, long-term impact, and innovation value guide resolution. This provides consistency under uncertainty.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI enhances training, clinical accuracy, and workflow efficiency. It also enables international knowledge exchange across pilot sites. Value creation is both clinical and organizational.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	AI adoption has led to new roles, integrated interdisciplinary teams, and deeper collaborations. Data and governance requirements have increased as a result. These changes reflect organizational transformation.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility directly shapes model architecture, data use, transparency, and deployment boundaries. Societal impact considerations constrain how and where AI is deployed.
18	Can you recall situations where AI required rethinking elements of the business model?	The organization shifted from AI products toward an enablement model. This includes infrastructure provision, capacity building, and multi-hub clinical validation. The change reflects a strategic business model reorientation.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	The Interviewee emphasizes that governance, rather than technology, is the main bottleneck in medical AI. Clinically led models are viewed as essential for safe and scalable AI.
20	May I contact you for clarification during analysis?	Yes. The Interviewee explicitly consents to follow-up contact via email.

Interview 13: Generative AI and Data Engineering Perspectives on Healthcare

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is an AI & Data Engineering Leader working at the intersection of AI, large-scale data and cloud infrastructures. He specializes in Generative AI, LLM systems and MLOps, and acts as a Cloud and Distributed Data Architect and Speaker. His professional role is thus directly and continuously linked to AI, digital technologies, and innovation in applied contexts.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	The Interviewee reports that AI adoption is typically driven top-down by organizational leaders reacting to hype and fear of missing out. Leadership compares themselves to other organizations' "success stories" and fears the "cost of opportunity lost" if they do not invest now. Large budgets are earmarked specifically for AI, and area leaders are then told to "do something with AI."
3	What external influences shape how AI is explored or adopted?	External influences include regulatory regimes and associated fines, which differ strongly by country. The Interviewee notes that some regulators are "really strict" and that high fines (e.g., a percentage of revenue) push companies to comply with GDPR/AI Act requirements, whereas others are more flexible and seek loopholes. In healthcare, additional sectoral regulations and the long-term sensitivity of health data make organizations especially cautious.
4	What internal conditions or capabilities affect how AI is approached?	Internally, leadership priorities, available budgets, and internal expertise shape AI adoption. Leaders may allocate budgets solely on the condition that they are spent on AI, leaving area leaders to decide whether to invest in technology, licences, hardware, or staff. In healthcare, strict internal governance and data constraints push teams toward AI in internal processes rather than direct patient-facing applications.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	In healthcare organizations the Interviewee has seen, patient protection and regulation override innovation opportunities. Review boards and governance structures simply block initiatives that fall into regulatory "grey areas" or might harm patients, even if they are innovative. This forces teams to abandon or redirect projects rather than "take the chance."
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	The Interviewee emphasizes that healthcare data remain sensitive regardless of time, as historical diagnoses (e.g., severe infections) can still harm individuals if leaked. Organizations in healthcare therefore face a "different game," combining GDPR/AI-Act-like rules with sector-specific laws and bias concerns. To uphold responsibility, they establish review boards and internal governance structures to ensure adherence to these norms.
7	How are potential impacts explored before implementing AI-related changes?	Potential impacts on patients are explored via strict rules that prohibit using AI in ways that might directly influence treatment when wrong predictions could cause harm. Governance boards scrutinize proposals and often stop projects that fall into ambiguous or risky areas. Because many patient-related features (including proxies) are disallowed, teams reassess whether there is "enough meat" to run AI at all.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection is largely embedded in governance processes. Boards ask systematic questions about model choice, data, proxy variables, use cases, testing, and drift, explicitly trying to avoid bias and proxy discrimination. For generative AI, the Interviewee also highlights the importance of explanation logs that justify outcomes, enabling teams to revisit assumptions if behaviour drifts.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	AI decisions in healthcare involve mixed review boards where experienced experts sit alongside individuals attracted by the topic's visibility and funding. The Interviewee notes that this creates "enterprise politics," with some participants contributing deep knowledge while others mainly seek to be associated with a high-profile area. Patients are not explicitly mentioned as direct participants, but their protection is central to board decisions.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical and societal considerations currently play a secondary role compared to feasibility: organizations are mostly focused on whether they can do something, not whether they should. The Interviewee expects that future regulation could limit workforce replacement, forcing companies to balance cost savings with employment preservation. He also anticipates debates about concentration of gains in a few AI vendors and the need for taxation or redistribution to avoid severe inequity.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	Decision-making around AI is structured through review boards that assess proposals sequentially: model choice, data, features, use case, testing, and monitoring. Projects are only approved if an appropriate model is used, datasets avoid bias and proxies, the use case is permitted, and testing and drift monitoring plans are robust. In healthcare, this process is described as "lengthy" but necessary.
12	What structures, roles, or processes support oversight of AI?	Oversight is supported by internal review boards and governance structures specifically set up to enforce compliance with regulations. These bodies evaluate model choices, data, and uses, and can block projects that do not meet standards. In healthcare, boards "sit down, check… effective value in the testing" before anything goes live.
13	How do you assess, document, or monitor potential issues with AI systems over time?	The Interviewee stresses the need to test models thoroughly before deployment and to monitor for drift afterward. Monitoring includes checking whether population or process behaviour changes over time and retraining or reprovisioning the model if it stops behaving as expected. For generative AI, he suggests storing justifications in logs so that unexpected outputs can be traced and reviewed.
14	When difficult decisions arise, how are they handled?	Difficult decisions often result in projects being stopped when risks to patients or regulatory concerns are deemed too high, even if the use case is attractive. Boards may also restrict use to internal, non–patient-facing processes to avoid ethical and legal conflicts. The Interviewee describes this as forcing teams to be more "creative" in finding safe applications.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	In healthcare settings he has seen, AI is mostly applied to internal organizational processes rather than direct patient care. This yields value primarily through cost reductions and process optimization (e.g., automating internal workflows), rather than new clinical services. He notes that AI is often framed as a means to "make more money or spend less money."
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	The Interviewee describes AI being used to automate tasks previously done by people, thereby reducing headcount and changing workforce composition. He gives the example of replacing a process run by 100 people so that only 20 are needed. Hybrid setups combining automation with large language models are expected, but the core effect remains cost savings via labour substitution.
17	How do considerations of responsibility or societal impact shape these changes?	Currently, responsibility and societal impact are not the main drivers of AI adoption decisions, which are dominated by cost and feasibility. The Interviewee anticipates that future regulations may restrict replacing workers and introduce obligations for redistribution, especially given the concentration of benefits in a few large AI vendors. He expects taxation or benefit-sharing mechanisms to emerge to prevent extreme inequality.
18	Can you recall situations where AI required rethinking elements of the business model?	No clear evidence of a specific, concrete business model pivot in a single organization. The Interviewee instead describes a general pattern in which organizations invest heavily in AI during hype phases, then later question return on investment, shrink budgets, and shut down initiatives that do not deliver value.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	In his outlook, the Interviewee expects a "pendulum" effect: after the current gold-rush phase, budgets will shrink and organizations will demand accountability and clear ROI from AI initiatives. He predicts a partial return to simpler, cheaper models where 97% accuracy is "good enough," rather than defaulting to expensive generative AI for every problem. He likens the current moment to previous technology waves (big data, neural networks, dot-com era).
20	May I contact you for clarification during analysis?	Yes. The Interviewee explicitly invites ongoing contact and expresses interest in reading the final thesis and staying in touch.

Interview 14: Pathology Innovator and AI Startup Consultant in Healthcare

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee is a pathologist by training with an oncology fellowship and a PhD in oncology, focused on digital pathology and translational medicine. He frames his role as "creating value from data," combining traditional pathology with digital and AI-enabled techniques to generate insights for startups, pharma, hospitals, and clinical trials.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	The Interviewee indicates that AI adoption emerged from the need to extract actionable insight from complex biomedical data rather than from a single triggering event. He emphasizes value creation from data as the primary motivation.
3	What external influences shape how AI is explored or adopted?	He highlights regulatory and cultural differences between Europe, the U.S., and China, arguing that premature regulation in Europe constrains experimentation. Market competition from large AI players (e.g., Big Tech) also shapes feasibility for startups.
4	What internal conditions or capabilities affect how AI is approached?	Internally, he stresses mindset, leadership, and risk tolerance as decisive. He argues that organizations often lack problem-focused thinking and MVP-driven execution, which limits effective AI use.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	No clear evidence. The Interviewee discusses regulation and ethics at a systemic level but does not describe concrete organizational routines for resolving such conflicts.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	The Interviewee rejects the notion of "responsible AI" as a property of the technology, arguing that responsibility lies with people using AI. He highlights the "black box paradox" and insists ethical accountability cannot be delegated to AI systems.
7	How are potential impacts explored before implementing AI-related changes?	No clear evidence. He argues conceptually for experimentation before regulation but does not describe formal impact assessments.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection is framed as learning-by-doing at a system level rather than through formal routines. He argues that uncertainty is unavoidable and must be accepted while observing outcomes before imposing constraints.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Stakeholders are implicitly framed as customers, patients, investors, and the public whose trust determines success. He stresses that losing patient trust due to poorly implemented AI has systemic consequences.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical considerations appear primarily through concerns about trust, misuse, and overpromising. He warns that deploying AI without solving real problems erodes credibility and public confidence.
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	No clear evidence. He criticizes leadership indecision ("I don't know") but does not outline formal AI decision-making structures.
12	What structures, roles, or processes support oversight of AI?	No clear evidence. Oversight mechanisms are not described; discussion remains at the level of critique of absent leadership and planning.
13	How do you assess, document, or monitor potential issues with AI systems over time?	No clear evidence. He does not mention audits, monitoring, or lifecycle documentation.
14	When difficult decisions arise, how are they handled?	He argues that leaders must provide plans (A, B, C) and actively manage risk rather than freezing. Failure to decide undermines authority and organizational trust.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	AI creates value only when it solves concrete problems (e.g., access, workflow, diagnostics). He rejects vague claims like "changing the world" without a clear value proposition tied to user needs.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	He emphasizes that startups should focus on MVPs that directly improve workflows (e.g., access to physicians, diagnostics). Without deployable products, AI does not translate into operational change.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility is linked to trust, credibility, and realistic promises. Overhyping AI without delivery damages societal acceptance and long-term adoption.
18	Can you recall situations where AI required rethinking elements of the business model?	He argues that AI business models must pivot from grand visions to problem-specific solutions (e.g., teleconsultation for access). This rethinking shifts focus from technology to necessity-driven services.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He closes by stressing mindset change, risk-taking, and leadership as prerequisites for meaningful AI innovation in Europe. He encourages continued dialogue to shift perspectives toward problem-solving.
20	May I contact you for clarification during analysis?	The Interviewee agrees and encourages follow-up discussion.

Interview 15: Data Scientist Leader in Healthcare AI Innovation

#	Guide Question	Summarized Answer
Warm-up		
1	Could you briefly describe your role and how it relates to AI, digital technologies, or innovation in your organization or professional context?	The Interviewee holds a PhD in electronics and communication engineering and has worked about eight years in healthcare AI. He started in telemedicine data security, then built AI-based breast cancer screening software (mammogram and ultrasound) in a Dubai startup. Since moving to Germany, he develops telemedicine solutions for orthopaedic diagnostics and rehabilitation and writes books on AI in healthcare. Recently he has focused on agentic and generative AI to build healthcare AI agents that reduce clinical operation time and support clinical note generation.
External & Internal Drivers of AI Adoption		
2	When your organization (or partners/clients) began working with AI, what factors most influenced this direction?	No clear evidence. The Interviewee describes his career trajectory and projects but does not specify triggering events or strategic priorities that initially drove AI adoption in any one organization.
3	What external influences shape how AI is explored or adopted?	He observes that regulatory environments and speed of processes differ by region. In India, solutions must be integrated quickly due to "lacks of doctors and huge number of people," whereas in Europe adoption is slower because of "lots of regulations" such as EU MDR. He notes that data protection laws are similar across India, UAE and Europe, but concrete steps like data collection may take 3 months in India and 6–9 months in Europe.
4	What internal conditions or capabilities affect how AI is approached?	Internally, effective AI development in diagnostics depends on close collaboration with doctors, who provide domain knowledge, define what to detect, and guide decision-relevant factors. The Interviewee stresses the need to translate technical outputs into medical context and to understand doctors' psychology and expectations for AI output. He also emphasises that AI must fit into existing clinical workflows and that trust-building is essential so doctors see AI as workload reduction rather than replacement.
5	How does your organization handle situations where innovation goals and compliance or ethical concerns conflict?	No clear evidence. The Interviewee compares regulatory timelines and emphasises the need for certificates and data security, but does not describe concrete routines or escalation processes for resolving conflicts between innovation and compliance within a specific organization.
Responsible Practices & Organizational Mechanisms		
6	How does your organization or professional environment address responsibility, ethical questions, or societal impacts?	Responsibility is addressed through strong collaboration with clinicians and through regulatory demands, especially on explainability. In diagnostics, doctors define which image features matter and what must be considered in decisions, and AI outputs must be interpretable (e.g. indicating where skin cancer is detected). The Interviewee underscores that healthcare has some of the "biggest regulations in the world," and that explainability of disease predictions is essential for safe use.
7	How are potential impacts explored before implementing AI-related changes?	Before rollout, the Interviewee evaluates both business and clinical impact. He examines how an AI solution fits existing healthcare business models (e.g. insurance-based payment flows) and how it improves diagnostic performance, such as detecting tumors that doctors might miss in breast cancer screening. These considerations guide whether and how to deploy AI.
8	In what ways do teams reflect on assumptions, uncertainties, or unintended consequences during AI development or use?	Reflection centres on continuous dialogue between technical and clinical perspectives. The Interviewee describes the need to convert technical language into medical context and vice versa, adapting AI design to disease type and patient condition. He notes that healthcare AI design, development and deployment differ by disease and patient context, and that it takes time to align AI tools with clinical expectations without threatening professional identity.
9	How are different groups or stakeholders involved in shaping AI-related decisions?	Besides doctors, regulators and certification bodies play a central role in healthcare AI. The Interviewee lists EU MDR in Europe, national digital health certificates in India, and authorities such as the Dubai Health Authority for UAE, which define which certificates are required to roll out products. These stakeholders shape decisions about whether and how AI solutions can be deployed.
10	Can you describe how ethical or societal considerations influence daily work with AI?	Ethical and societal considerations influence daily work via requirements for explainability and human-in-the-loop decision-making. The Interviewee insists that AI remain a supportive tool and that doctors must ultimately decide how to treat patients. He warns that direct-to-patient AI for self-medication is harmful and argues that AI solutions should reach patients only through proper channels (hospitals or doctors) because AI-driven decisions can be "taking your life."
Governance of AI (RAI)		
11	How is decision-making around AI organized in your organization or projects?	He describes governance mainly in terms of data protection and infrastructure constraints rather than internal committees. In Europe, GDPR and national rules mean he cannot "communicate directly with the hospitals"; instead, AI must be deployed on-premise or via certified telematics cloud infrastructure defined by authorities. By contrast, private hospitals in Dubai and India can adopt solutions more quickly within government data security rules.
12	What structures, roles, or processes support oversight of AI?	Oversight is exercised by regulatory and certification structures (e.g. EU MDR, national digital health authorities) and by mandated infrastructures such as telematics cloud services. These define how and where AI systems may be hosted and accessed, functioning as control points for deployment.
13	How do you assess, document, or monitor potential issues with AI systems over time?	No clear evidence. The Interviewee does not describe validation protocols, documentation standards, audits, or ongoing monitoring of AI performance or safety.
14	When difficult decisions arise, how are they handled?	No clear evidence. He speaks about frustrations with slow processes in Europe and differences across regions but does not explain how specific difficult decisions are escalated or resolved.
Implications for Business Models		
15	In what ways has AI influenced how value is created or delivered in your organization or sector?	He sees AI influencing value mainly through efficiency gains and new tools that speed documentation and decision support. A prominent example is AI-powered clinical note generation, where doctor–patient conversations are recorded and converted into clinical notes using LLMs and speech-to-text, already rolled out in many parts of the world, including Germany (e.g. "Dragon Copilot"). In diagnostics (e.g. breast cancer), AI adds value by helping detect tumors that doctors might miss.
16	What changes in workflows, roles, capabilities, or partnerships have resulted from AI adoption?	Workflow changes include reduced manual documentation and faster access to patient information. AI agents and LLM-based tools are expected to help doctors analyse their own data, retrieve previous cases, and access prior research directly from systems, thereby reducing operational time. The Interviewee notes that many tasks currently done physically (e.g. checking paper files) can be replaced by querying an AI agent integrated with hospital records.
17	How do considerations of responsibility or societal impact shape these changes?	Responsibility concerns shape design choices about who AI is built for and how it reaches patients. The Interviewee argues that many people fear AI will take their jobs and calls for regular sessions in public hospitals to show how AI can help rather than threaten them. He warns that direct-to-patient AI enabling self-medication is harmful and insists solutions should go through proper clinical channels, because wrong AI advice can affect a person's life.
18	Can you recall situations where AI required rethinking elements of the business model?	No clear evidence. The Interviewee notes that healthcare is also a business with money flows via insurance and considers business impact when deploying AI, but he does not describe specific cases where AI forced changes to revenue models, patient pathways, or service integration.
Closing		
19	Is there anything important about AI, innovation, or responsibility that we have not discussed?	He highlights the need for ongoing education of public hospitals and institutions about how AI can be useful and what to consider when designing healthcare AI. He criticises solutions that target patients directly and bypass clinical oversight, arguing that such offerings can be harmful if patients follow AI-prescribed medication without consulting a doctor. He stresses that AI should be channelled through hospitals or doctors to protect patients' lives.
20	May I contact you for clarification during analysis?	Yes. The Interviewee explicitly agrees to further contact and discussion after the thesis is completed and invites follow-up.

Appendix E - Gioia First-Order Concepts

Concept	Quote	Definition	Interview
ChatGPT as everyday clinical research assistant	"Uses AI, particularly ChatGPT, for faster research in everyday clinical work."	Use of ChatGPT to speed up information search in daily clinical work	Interview 1
Dual role as clinician and AI startup contributor	"Additionally… involved in a not-yet-founded AI startup."	Physician role plus involvement in building an AI startup	Interview 1
Tumor board decision support with partial automation	"Focusing on partially automating tumor board decisions."	Startup goal to partially automate tumor board decisions	Interview 1
Emphasis on EU-compliant data protection in startup	"Goal… while ensuring EU-compliant data protection."	Startup explicitly oriented to EU data protection compliance	Interview 1
AI seen as major trend in medicine	"AI is currently seen as a major trend in medicine."	AI perceived as a dominant trend motivating experimentation	Interview 1
AI enables fast, easy-to-publish research	"AI enables fast-paced research with simple study designs that are easy to publish."	AI allows simple study designs and quick publications	Interview 1
Visibility and career opportunity drive AI engagement	"This combination of visibility, momentum, and research opportunity acts as a primary driver."	Research visibility and habilitation prospects motivate AI use	Interview 1
Limited time and regulatory capacity at employers	"Limited time and lack of regulatory capacity in medical employers shape how AI is used."	Employers lack time and regulatory staff to structure AI	Interview 1
Anonymized diagnosis lists tested in ChatGPT	"Clinicians sometimes paste anonymized diagnosis lists into ChatGPT."	Clinicians test ChatGPT with anonymized diagnosis lists	Interview 1
Perceived ~80% diagnostic accuracy	"AI is said to reach around '80% accuracy."	AI performance roughly estimated at 80% accuracy	Interview 1
Data protection seen as essential baseline	"Data protection is emphasized as essential."	Data protection emphasized as necessary condition for AI use	Interview 1
Organization invests few resources in AI for daily work	"The organization invests few resources into AI for everyday physician work."	Employer does not actively support AI integration in routine tasks	Interview 1
Time scarcity as central barrier	"Time scarcity is a central internal barrier."	Lack of time in clinical work impedes structured AI adoption	Interview 1
Physicians self-initiating AI use	"Physicians must proactively integrate AI tools themselves."	Individual doctors integrate AI tools on their own initiative	Interview 1
Bottom-up AI adoption without strategy	"AI adoption is thus bottom-up driven."	AI use emerges from individual experimentation, not organizational plan	Interview 1
Absence of guidelines for innovation–ethics tensions	"There are no organizational guidelines for managing tensions between innovation and compliance/ethics."	No formal guidance on how to resolve innovation vs compliance/ethics conflicts	Interview 1
No formalized approach to AI-related conflicts	"There is no specific or formalized approach to such situations."	Lack of specific procedures for dealing with conflicts involving AI	Interview 1
Responsibility and ethics implicitly reduced to data protection	"Responsibility and ethics are only implied… mostly in relation to data protection and the assumption that systems are compliant."	Responsibility framed mainly as data protection and compliance assumptions	Interview 1
Lack of time for explicit ethical reflection	"There is no time to consider ethical issues."	Time constraints prevent engaging with ethical/societal questions	Interview 1
No structured pre-implementation impact assessment	"The Interview does not describe structured pre-implementation impact assessments."	Absence of systematic evaluation of clinical/ethical impacts before AI use	Interview 1
Informal testing of free LLMs with guideline scenarios	"Clinicians test free LLMs with guideline-based scenarios, but without formalized evaluation."	Clinicians test free LLMs against guidelines without formal evaluation	Interview 1
Informal collegial exchange normalizes AI use	"Reflection occurs informally through collegial exchange."	AI use spreads via everyday exchange among colleagues	Interview 1
Translation use case as AI entry point	"Initial AI adoption emerged when a Venezuelan colleague used AI for translation."	Early AI use focused on translation by foreign colleague	Interview 1
ChatGPT provides quick answers to complex questions	"ChatGPT provides quick answers to complex questions."	LLM offers rapid answers that are then checked	Interview 1
Retrospective source checking as 'open evidence' loop	"Sources checked afterwards ('open evidence'), representing a loose retrospective validation loop."	Physicians check sources after AI output as loose validation	Interview 1
Physician-dominated AI decision-making	"Decisions appear to be made predominantly by physicians."	Physicians are the main (implicit) decision-makers on AI use	Interview 1
No formal stakeholder involvement in AI decisions	"The Interview does not identify formal stakeholder involvement."	Absence of structured involvement of other stakeholder groups	Interview 1
No perceived ethical concerns due to time pressure	"There are no ethical concerns… mainly because time constraints prevent deeper engagement."	Ethical concerns not articulated because there is no time	Interview 1
Data protection conformity assumed by default	"Data protection conformity is generally assumed."	Compliance with DP rules is taken for granted, not examined	Interview 1
Physician expertise and authority remain primary	"Physicians rely on their expertise and maintain decision authority."	Clinicians retain decision authority despite AI use	Interview 1
AI viewed as supportive knowledge tool, not decision-maker	"Viewing AI primarily as supportive knowledge rather than decision-making automation."	AI understood as information aid, not automated decider	Interview 1
Case-specific clinical decision-making	"Each patient is treated as a unique case."	Each patient treated as unique; AI does not standardize decisions	Interview 1
AI used for idea generation and scoping literature	"AI serves mainly for idea generation and narrowing research scope."	AI used to generate ideas and narrow research scope	Interview 1
No automated or AI-based final decisions	"Final decisions are always made by physicians. No automated or AI-based decisions occur."	Final clinical decisions are always human-made	Interview 1
No formal AI oversight structures or roles	"No structures, roles or processes exist to oversee AI activities."	No committees, roles, or processes for AI oversight	Interview 1
No lifecycle governance for AI systems	"No established processes for evaluating, documenting or monitoring issues… No lifecycle governance mechanisms are in place."	No evaluation, documentation or monitoring over time	Interview 1
Humans handle difficult decisions without AI	"Difficult decisions are ultimately made by humans, especially physicians."	Critical decisions, especially high-stakes, are made without AI	Interview 1
AI-generated drafts used as templates for presentations	"For presentations, AI-generated drafts… are used as templates."	AI is used to create initial drafts that are later edited	Interview 1
Sources checked and content revised after AI drafts	"Sources are subsequently checked and content revised."	Human review and revision of AI outputs	Interview 1
AI avoided in high-stakes qualification decisions	"Critical decisions with implications for specialist qualifications are always made without AI."	AI not used where specialist qualification is at stake	Interview 1
AI used only in rare diagnostic edge cases	"AI is used only in rare diagnostic edge cases."	AI used selectively for unusual diagnostic situations	Interview 1
AI streamlines information retrieval	"AI shortens research workflows… Value creation appears in streamlined information retrieval."	AI accelerates search for relevant information	Interview 1
Faster access to relevant studies and papers	"Leading more quickly to relevant studies and papers."	AI leads more quickly to relevant evidence	Interview 1
AI structures complex issues for faster comprehension	"Used to present complex issues in a clear and structured way, thus enabling faster comprehension. "	AI helps present complex issues clearly and quickly	Interview 1
Perceived faster and higher-quality decisions vian AI	"Therefore, AI leads to faster and higher-quality decisions, although… a perceived effect."	AI believed to improve speed and quality of decisions (unmeasured)	Interview 1
AI frees physicians' time for targeted specialist research	"Freeing up the doctor's time to research relevant specialist sources."	AI summarization allows time to go deeper into specialist sources	Interview 1
AI supports translation and understanding documentation	"It is also used by foreign physicians for translation and understanding patient documentation."	AI used by foreign physicians for language and comprehension	Interview 1
AI reduces language barriers for foreign physicians	"This reduces language barriers and accelerates clinical and research tasks.	AI decreases language-related friction in clinical work	Interview 1
Hardly any time for responsibility or societal reflection	"There is hardly any time in clinical work to consider responsibility or societal implications."	Time constraints block reflection on societal implications	Interview 1
AI used with some caution but minimal reflection	"AI is used 'with some caution,' but without deeper reflection."	AI is used carefully but without systematic ethical debate	Interview 1
Responsibility embedded in individual physician judgement	"Responsibility remains primarily embedded in physician decision-making rather than formal processes."	Responsibility located in physician decision-making, not structures	Interview 1
Productivity tools like Copilot imagined as helpful	"Tool such as Microsoft 365 Copilot… would ease daily work."	Integrated AI tools (e.g., Copilot) seen as potentially easing work	Interview 1
AI-driven business model changes remain hypothetical	"However, the example is hypothetical, and no concrete business model changes are described."	No concrete changes to business model; only imagined	Interview 1

Concept	Quote	Definition	Interview
Legal frameworks like EU AI Act seen as important	“Highlights the importance of legal aspects (e.g., the EU AI Act).”	Legal regulation perceived as central to AI discussions	Interview 1
Free LLMs tested against guidelines and regulations	“Many free LLMs are tested against guidelines and regulations.”	LLMs informally compared to guidelines	Interview 1
Underlying studies too complex for AI to fully capture	“Underlying studies are highly complex and often exceed what AI can capture.”	AI perceived as not capturing full study complexity	Interview 1
AI perceived as 'black box'	“Reinforcing that AI remains a ‘black box.”	AI seen as opaque in its reasoning	Interview 1
Belief that data cannot really be misused because AI does not flag non-compliance	“Feeling that data cannot really be misused, since AI does not flag non-compliance.”	Paradoxical perception of low misuse risk due to lack of warnings	Interview 1
Healthcare AI spans trivial to high-risk	“Everything from… Apple Watch… all the way to a surgical robot.”	AI in healthcare ranges from wellness devices to semi-autonomous surgical robots, with very different risk profiles.	Interview 2
"AI" label often misused for clever algorithms	“A lot of what is AI is just clever algorithms… data management is called AI because it raises money.”	Many systems sold as "AI"are conventional analytics, rebranded for fundraising or marketing.	Interview 2
Different buckets of sensitive information	“Patient data… staff faces… that's not patient data, but it's sensitive information.”	Sensitivity varies (patient data, staff data, OR images) and must be categorized differently.	Interview 2
Passive vs agentic AI distinction	“Is it just being passive… or is the AI… moving a robot's arm?”	Distinguishes AI that only analyses data from AI that directly acts on the physical world.	Interview 2
Need to bucket AI systems by sensitivity and agency	“You have to start bucketing it… each… has different regulations and different ethical issues.”	Calls for classification of AI into risk categories based on sensitivity and degree of autonomy.	Interview 2
Legal liability largely covered by existing product/consumer law	“If any product is defective… there's a lot of law that already covers that.”	Argues that many AI liability questions are already addressed by existing product/consumer law.	Interview 2
Distinct legal, regulatory and ethical layers	“That gets us into three things, regulatory, ethics, and legal.”	Frames AI governance as three partially overlapping regimes: regulation, law, ethics.	Interview 2
Global regulatory divergence in AI for devices	“FDA is very advanced… Europe's struggling… China… embracing it at full power… doesn't know what it's doing.”	Highlights differing maturity and approaches of major regulators (US, EU, China).	Interview 2
Surgeons' attitudes range from eager to resistant	“You'll go from… ‘I need all the help I can get’… to ‘I'm too good for that.’”	Describes spectrum of clinician attitudes to AI, from enthusiastic adoption to rejection.	Interview 2
AI as "today's fancy word" and hype driver	“Today's flavor… Let's get AI in everything.”	Sees AI as a buzzword that organizations rush to adopt for image and KPIs.	Interview 2
Top-down AI tools imposed without consultation	“Here's your new AI tool, plug it in… there is a lot of resistance.”	Describes hospitals introducing AI from the top without involving users.	Interview 2
Lack of consultation across ecosystem	“Industry's not consulting enough with the healthcare providers… hospitals… with the users… users… with the patients.”	Identifies missing consultation between industry, hospitals, users, and patients.	Interview 2
Need for fast but structured consultation framework	“There needs to be a framework of consultation… fast, but there needs to be a framework.”	Argues for formalized but agile consultation structures for AI introduction.	Interview 2
Good firms delay AI to co-design with users	“Some of the good companies doing it well… consulting very deeply with their users.”	Notes that responsible firms prioritize consultation before pushing AI features.	Interview 2
Error reduction as primary near-term AI value	“The #1 aim… is error reduction.”	Frames error reduction as the central objective for clinical AI.	Interview 2
AI as radiology second reader / second opinion	“AI… in parallel… both say ‘tumor’ or not… you've had a second set of eyes.”	AI provides a second opinion, prompting reconsideration rather than overriding clinicians.	Interview 2
Human-in-the-loop to resolve AI–clinician disagreements	“It's not that the AI wins… it's… ‘are you sure?’ and the radiographer looks deeply.”	Emphasizes human review when AI and clinician disagree, preserving human responsibility.	Interview 2
AI can misclassify rare patterns (button as tumor)	“AI has never been trained what a button looks like… said it was… a tumor.”	Illustrates AI blind spots when training data lack rare but benign artifacts.	Interview 2
AI should augment, not replace, clinicians (10-year horizon)	“I think the solution becomes human augmentation, not replacement for the next 10 years.”	Advocates augmentation as the realistic and ethical paradigm in the medium term.	Interview 2
AI reduces administrative burden and focuses search	“Value… removing administrative burden… finding… ‘look at these five papers’.”	AI is most useful for documentation, organizing data, and narrowing literature search.	Interview 2
Implementation pathway as crucial as technology	“As much as the technology is important, the pathways of introduction are important.”	Stresses that success depends on how AI is introduced, not only on its technical quality.	Interview 2
Technology gold rush → tragedy → governance pattern	“Introduced, gold rush, tragedy happens, review, now put… governance in place.”	Describes a recurring cycle where governance follows crises rather than preceding them.	Interview 2
Governance resources lag behind AI investments	“Put as much resources into… governance… as… into the AI itself.”	Argues resource allocation to governance should match investment in AI technology.	Interview 2
Lack of time for peer knowledge exchange	“Surgeons… don't have time to exchange… it's just for me… can't write it down.”	Acknowledges that clinicians lack time and structures to share AI-related learning.	Interview 2
Emerging backbone infrastructures for knowledge capture	“Gather all that knowledge… video… EMRs… cloud… intelligent systems dig out the insights.”	Notes new platforms capturing surgical video and data to surface useful insights.	Interview 2
Rating and surfacing best insights (Airbnb analogy)	“Give it a zero to five star rating… like Airbnb… bubbles to the top.”	Illustrates crowd-rating mechanisms to prioritize valuable AI-derived insights.	Interview 2
Commercialization paradox: users won't pay for their own knowledge	“Why would I pay you to tell me what time it is when I can just look at my watch?”	Describes difficulty monetizing AI insights when clinicians feel they "already know"the content.	Interview 2
Evidence gap on AI's real impact	“You'll see thousands of papers saying… great… and… no value… no one's collected that data yet.”	Points to lack of robust evidence that AI insights improve outcomes or reduce costs.	Interview 2
AI as future necessity due to workforce shortage	“Baby boomer… every year we're losing people… AI is definitely going to become mandate.”	Views AI as necessary to cope with future workforce shortages (e.g., stroke treatment).	Interview 2
Budget myopia blocks proactive AI investment	“My budget today… gets spent this year… how can I spend… on stuff… 10 years time?”	Explains why systems struggle to invest now for future AI needs.	Interview 2
Ethical obligation to future patients	“What obligation do we have today to protect the future generation of tomorrow?”	Raises intergenerational ethics around AI and healthcare infrastructure decisions.	Interview 2
Bridge-builder between technology and practice	“I see myself as a bridge-builder between technology and practice.”	The Interview's self-conception as someone who connects technological solutions with real-world clinical and organizational practice.	Interview 3
Demographic change and staff shortages as AI drivers	“He thought about patient care with demographic change and staff shortages in mind.”)	Perception that ageing populations and healthcare workforce shortages are central drivers for adopting AI.	Interview 3
Automating repetitive tasks to relieve system pressure	“For repetitive tasks, maybe technology can help take some pressure off the system.”	View that AI should target repetitive work to reduce workload and systemic pressure in healthcare.	Interview 3
Improving quality through cleaner medical documentation	“He saw how missing or poorly written letters can harm patients in the long run.”	Belief that AI can help ensure clean, complete documentation to support long-term care quality.	Interview 3
Supporting migrant doctors with language and documentation burden	“Doctors with a migration background face huge pressure to write perfect letters in 24-hour shifts.”	Recognition that AI can assist foreign-trained physicians who struggle with language and documentation demands.	Interview 3
Tech-first, ROI-driven AI adoption logic	“Often the goal is to introduce technology quickly to get a fast return on investment.”	Critique that organizations start from ROI and tools rather than from problems and business cases.	Interview 3
Tool selection before clarifying business case	“They choose the tool first and then try to work backwards to the business case.”	Pattern of starting with a specific AI tool and only afterwards searching for suitable use cases.	Interview 3
Low adoption due to poor explanation and fears	“After months they wonder why adoption is low; technology wasn't explained, fears remain.”	Insight that lack of communication about AI creates fear (data, jobs, transparency) and weak adoption.	Interview 3
Employee concerns about data, transparency, and job security	“People worry: what happens to data, how does the model learn, will my work be replaced?”	Employees' concerns around data use, model opacity and possible substitution of their work.	Interview 3
Human–technology–data transparency as critical success factor	“The factor ‘human plus data plus transparency’ plays a huge role.”	Emphasis on combining human factors, data handling, and transparency as key to responsible AI use.	Interview 3
High failure rate of AI projects due to shortcut mentality	“Studies say around 90% of AI projects fail because people look for a blueprint.”	Belief that many AI projects fail because organizations seek easy templates instead of doing hard contextual work.	Interview 3
Need for heterogeneous, cross-functional AI project teams	“The real answer is to build a heterogeneous team that works from business cases.”	Advocacy for diverse teams considering multiple perspectives when designing AI initiatives.	Interview 3
Regulatory strictness in healthcare as justified barrier	“In healthcare we have strict regulations and high responsibility for living beings.”	View that strong medical device and data regulations are legitimate constraints on AI adoption.	Interview 3
Leadership and culture as key internal enablers	“Leadership and internal culture are extremely important – error culture, trying things out.”	Emphasis on leadership, learning culture, and openness to experimentation as prerequisites for AI success.	Interview 3
Co-creation and continuous competence development	“Co-creation and continuous competence development are crucial, especially for leaders.”	Stress on leaders and staff co-creating AI solutions while continually developing AI-related skills.	Interview 3
Purely monetary expectations as red flag for AI projects	“If expectations are purely monetary, that's a red flag – we shouldn't start under those conditions.”	Argues that narrow financial motivations signal problematic AI projects lacking broader responsibility focus.	Interview 3
Building internal AI "community of practice"	“I need people who burn for this, build a community in the organization.”	Idea that internal communities of AI enthusiasts can pull along colleagues with fears and doubts.	Interview 3
Holistic 360° approach and admitting limits	“We need a holistic 360-degree view and honesty to bring in external competence if needed.”	Call for holistic perspective and willingness to buy or hire missing expertise rather than pretending competence.	Interview 3
Cheapest-solution bias undermining responsible AI	“The primary goal was to choose the cheapest solution for a self-check-in system.”	Observation that clients often favor low-cost AI solutions without fully considering legal and ethical aspects.	Interview 3

Concept	Quote	Definition	Interview
Unawareness of GDPR and legal responsibilities	"I noticed a lot of unawareness about GDPR and legal frameworks on the customer side."	Many decision-makers lack basic understanding of data protection and legal obligations in AI deployment.	Interview 3
Lack of basic AI literacy among decision-makers	"They often lack basic know-how to even make a decision."	Problem that people tasked with AI decisions do not have sufficient AI literacy or experience.	Interview 3
Historical or accidental appointment of AI decision-makers	"They are in the role for historical reasons or because they didn't duck away fast enough."	AI responsibilities sometimes land on people by chance rather than by competence or mandate.	Interview 3
Need for maturity assessments before AI projects	"We run maturity assessments; if an organization is in the lower third, some topics are off the table."	Suggestion to measure organizational readiness and postpone or reshape AI projects when maturity is low.	Interview 3
Desire for evidence-based decisions over gut feeling	"Instead of gut feeling, I want evidence-based data showing where we stand and what to do."	Preference for data-informed AI decisions and stakeholder views rather than intuitive or ad hoc choices.	Interview 3
Time pressure and perceived inability to involve stakeholders	"People say: I'm under so much time pressure, I can't afford to run such analyses."	Recognition that time constraints are used as justification for skipping stakeholder and risk analyses.	Interview 3
Middle managers feeling compelled to follow orders	"They sometimes feel almost forced to do it and don't question the project towards top management."	Middle-level staff may comply with AI projects despite reservations, avoiding conflict with leadership.	Interview 3
Neglected employee participation in AI design	"Employee involvement is a big topic; we should interview people from different units about pain points."	Emphasis that staff perspectives on processes and pain points are often missing from AI project design.	Interview 3
Best practice: dedicated change managers and UX with domain experts	"Some bring together change managers, UX/UI people, developers, and the specialist department around a business case."	Description of good practice where cross-functional teams co-design AI around concrete business cases.	Interview 3
Importance of executive sponsorship for AI change	"Ideally someone from top management is involved to provide commitment and radiate it internally."	Need for visible leadership support to legitimize AI initiatives and change efforts.	Interview 3
IT should not be sole driver of AI projects	"IT says: it should run, but initiatives must come from the business units, IT can't lead everything."	Position that AI projects should be driven by business units, with IT supporting rather than leading.	Interview 3
Governance as living, evolving document	"Governance must be a living document, updated with lessons from the first project onwards."	Concept of AI governance as iterative, regularly revised and grounded in project experience.	Interview 3
Early, practice-based governance rather than abstract rules	"Setting it up purely beforehand is difficult; too far from practice, you block yourself."	Belief that governance should grow with real use cases instead of being purely theoretical ex ante.	Interview 3
Using internal LLM "governance bots" for policy access	"You could implement an LLM governance bot so people can ask: what is our process?"	Idea of leveraging LLMs to make governance rules more accessible and queryable for staff.	Interview 3
External monitoring layers to detect compliance and shadow AI	"Vendors offer monitoring layers reading systems to see if you are compliant or have shadow AI."	Description of tools that monitor infrastructure to detect non-compliant or unofficial AI use.	Interview 3
Risk of staff using unofficial AI tools (shadow AI)	"If we don't regulate what's used, people say: I'll just use my own GPT-5."	Concern that inadequate official tools or governance lead employees to circumvent rules with private AI.	Interview 3
AI for speech-based documentation and coding support	"Doctors want to speak during consultations and have systems transcribe, anonymize and set billing codes."	Main practical AI use case: automating transcription and coding to reduce documentation burden.	Interview 3
AI as support to free time for core medical work	"Goal is to free trained professionals so they can really focus on medicine and people."	View that AI should reduce administrative overhead so clinicians can spend more time on patient care.	Interview 3
Path of least resistance leads to shadow IT (e.g., WhatsApp)	"People choose the path of least resistance: WhatsApp groups, etc., which is problematic for security."	Recognition that staff use consumer tools for convenience, creating security and compliance risks.	Interview 3
Diverse development teams reduce bias in AI systems	"The more homogeneous the team, the more homogeneous the software and its biases."	Belief that heterogeneous dev teams help mitigate bias and irritation from AI outputs.	Interview 3
Need to train users on language and bias in AI interactions	"We must train people on language use with AI; otherwise results will irritate them."	Call for user education about how prompts, language, and underlying data shape AI outputs.	Interview 3
Risk of trust erosion when AI outputs surprise users	"If things don't work, people easily reject the whole technology instead of questioning data or design."	Concern that unexpected AI outputs can lead to broad rejection rather than nuanced critique.	Interview 3
AI literacy as societal goal by 2030	"My North Star is contributing to AI literacy by 2030."	Ambition to raise AI understanding at scale as a precondition for responsible adoption.	Interview 3
AI as inevitable and needing "AI for good" framing	"It's inevitable; we have no choice but to engage and use it for AI for good."	Framing AI as unavoidable, making responsible, beneficial use the key challenge.	Interview 3
Demographic peak of workforce shortage as AI pressure	"Around 2030–2032, five million workers will be missing in Germany."	Expectation that severe labor shortages will increase pressure to use AI in healthcare.	Interview 3
International competition for skilled healthcare workers	"Foreign professionals can choose countries; there is competition over where they go."	Recognition that attracting foreign healthcare workers is competitive, limiting this mitigation option.	Interview 3
Hospital consolidation and economic pressure	"We already see consolidation: large hospitals absorb smaller ones that are not viable."	Observation that structural changes in the hospital landscape intensify the need for efficiency.	Interview 3
AI as one important lever among others	"AI is one of the levers we have and should use, alongside other important measures."	Positioning AI as a key, but not sole, mechanism to address systemic challenges in healthcare.	Interview 3
Regular use of two main AI applications	"There are two big applications that I use regularly."	The Interview's AI use in daily work is centred on two concrete tools rather than a broad toolset.	Interview 4
AI app for EKG-based heart-attack detection	"There is an app that interprets ECGs for infarct detection."	Use of a specialized AI (PM Cardio) that analyses ECGs to support myocardial infarction diagnosis.	Interview 4
AI detects subtle EKG changes better than doctors	"The AI does this overwhelmingly well… better than our experienced senior consultants."	Perception that the ECG AI outperforms even experienced cardiologists in detecting infarct patterns.	Interview 4
Smartphone photo workflow for AI ECG interpretation	"You scan the ECG, send a photo and get a result."	Practical use pattern: photographing ECG printouts and submitting them to the AI app for interpretation.	Interview 4
Use of Open Evidence for validated study summaries	"You can find very validated information on current study data."	Reliance on an evidence platform (Open Evidence) that aggregates and summarizes high-quality medical literature.	Interview 4
AI helps navigate overwhelming journal landscape	"There are so many journals… you can't keep up anymore."	AI is used to cope with information overload in medical publishing and stay up to date.	Interview 4
AI supports dosing and therapeutic decisions	"You can quite well look up, for example, maximum ACE inhibitor dosage."	AI evidence tools are used to check dosages and therapeutic details for specific conditions.	Interview 4
Senior chief physician sceptical toward digital tech	"My boss… is not a digital native… he is sceptical about such technology."	The head of department belongs to an older generation and is generally sceptical of AI-based tools.	Interview 4
Distrust of AI vendor due to Eastern European base	"The app has links to Eastern Europe… that is suspicious."	Geographic origin of the vendor fuels suspicion and reduces leadership support for the AI app.	Interview 4
Autodidactic, bottom-up AI adoption by residents	"It's more autodidactic… it all comes from us residents."	AI use is driven by junior doctors rather than introduced through formal top-down programmes.	Interview 4
Open-minded consultants as AI allies	"Partly inputs from consultants who are a bit more open-minded and look around."	Some senior physicians with more openness to innovation informally support AI use.	Interview 4
Conference encounter with AI developer triggers adoption	"A colleague met one of the developers at a cardiology congress."	Personal contact at a conference with a renowned cardiologist involved in the app spurred local adoption.	Interview 4
Peer recommendation as diffusion mechanism	"Since then this colleague recommends the app to everyone he knows."	Spread of the AI app within the department occurs mainly via informal peer recommendation.	Interview 4
Employer refuses to pay for clinical AI license	"The licence costs about 240 euros per year… my employer won't pay."	The hospital does not fund the ECG AI licence, despite its perceived clinical value.	Interview 4
Use of private smartphones for clinical AI ("shadow AI")	"So we do it with our private phones."	Residents use personal devices to run AI tools for clinical work outside formal IT governance.	Interview 4
AI use lacks organisational governance and documentation	"There is nowhere documented that we may use it or rely on it."	AI use is neither formally authorised nor recorded in institutional policies or patient documentation.	Interview 4
Human retains full responsibility for decisions	"We can never offload responsibility. We are ultimately responsible."	Clinicians see themselves as fully accountable for decisions, regardless of AI involvement.	Interview 4
AI suggestions sometimes overridden by clinical context	"There are cases where we decide differently because other factors play a role."	AI outputs are not followed blindly; contextual factors can lead to different decisions.	Interview 4
AI treated as idea generator, not decision-maker	"The AI is for generating ideas, but not more than that."	AI tools are used to inspire and orient thinking rather than to make final clinical decisions.	Interview 4
Generative AI training prohibits public tools	"The training said: you may not use publicly available generative AI."	Formal training at the medical school forbids the very public AI tools clinicians actually use.	Interview 4
Formal AI training perceived as medico-legal, not practical	"I questioned whether the training reflects reality or just covers medico-legal aspects."	The Interview sees official training as disconnected from everyday practice and mainly risk-avoidant.	Interview 4
Open Evidence used for orientation then verified	"We often read the original literature again… we use it for orientation."	AI evidence tools provide an initial direction, but clinicians still verify information in primary literature.	Interview 4
AI used to refresh knowledge and update evidence	"I use it not to replace my knowledge, but to refresh or update it."	The cardiologist uses AI to recall and update knowledge gained in training, not as a substitute.	Interview 4
AI not yet used personally for documentation	"For documentation I don't use it yet. I know some do."	The Interview has not (yet) adopted AI for writing reports, though he sees the potential.	Interview 4
No formal AI-related decision process	"There is no fixed decision-making process for how this runs."	Decisions involving AI are not embedded in structured organisational pathways or protocols.	Interview 4
Informal culture of collegial consultation for tough cases	"For really important things we would rather talk to several colleagues."	Difficult decisions are handled through collegial discussion rather than reliance on AI systems.	Interview 4
Research context more open to admitting AI use	"In research nobody needs to be ashamed to say: 'I used ChatGPT for spelling."	AI use is more openly acknowledged and accepted in research activities than in clinical care.	Interview 4

Concept	Quote	Definition	Interview
Generative AI accelerates coding and statistics work	“He lets ChatGPT write his R prompts and gets along really well.”	Generative AI is used to produce statistical code, easing barriers to tools like R.	Interview 4
AI supports higher-quality rather than faster work	“I can't say I'm faster… higher quality I can rather imagine.”	Perception that AI use may raise decision quality more than it reduces time.	Interview 4
Efficiency gain as handling more tasks, not time saving	“I maybe have an efficiency advantage so that I manage more things.”	AI allows the clinician to accomplish more work, even if individual tasks are not demonstrably faster.	Interview 4
Future AI potential in coronary angiography image analysis	“In future a KI will support us in interpreting the angiography images.”	Expectation that AI will analyse moving coronary images and assist in judging stenosis relevance.	Interview 4
AI could recommend stent type, size and inflation pressure	“It could also suggest which stent, what pressure, how long it has to be.”	Imagined AI decision support for interventional therapy planning in cardiology.	Interview 4
Existing hospital-wide AI for chest X-ray analysis	“For every thorax X-ray… there is already a KI report.”	The university hospital has deployed an AI that automatically analyses chest radiographs.	Interview 4
Thorax AI performance currently judged as poor	“I find it not good yet. We often have a different opinion.”	The clinician experiences the existing CXR AI as low quality and often disagreeing with human judgement.	Interview 4
Official AI outputs explicitly require human review	“You get: this is what the AI said, please assess it yourself.”	The hospital's AI reports are framed as suggestions, with explicit instruction for human assessment.	Interview 4
Partial transparency about AI training data builds trust	“I know they used tens of thousands of ECGs with cath films.”	Knowing something about the training dataset of the ECG AI increases the Interview's trust in it.	Interview 4
Lack of transparency about other AI tools	“With Open Evidence, for example, I don't know how it works.”	In contrast, the mechanisms behind some AI tools remain opaque to the user.	Interview 4
Informal knowledge exchange spreads understanding of AI origins	“This knowledge came because my colleague was so involved.”	Understanding of AI training and design spreads via informal collegial conversations.	Interview 4
Patients increasingly use ChatGPT for self-information	“Patients also use it… they come quite well informed with problems.”	Patients use freely available AI (e.g., ChatGPT) to research their conditions before consultations.	Interview 4
Patient AI research sometimes correct and helpful	“They sometimes also are right and have helpful ideas.”	Clinicians occasionally find that AI-informed patient suggestions are clinically valid.	Interview 4
Non-disclosure of AI use to patients	“I don't tell the patient why I made my decision.”	The cardiologist typically does not disclose that AI tools contributed to diagnostic reasoning.	Interview 4
AI used as confirmation of pre-existing diagnostic concept	“I already have a concept in mind and just seek confirmation.”	AI is mainly used to confirm or support a clinician's initial diagnostic hypothesis rather than to generate it.	Interview 4
Hospital-introduced AI medication system	“We bought a program… Apennio… introduced by the hospital.”	AI-enabled medication/documentation system was procured and introduced top-down by the hospital, not by clinicians.	Interview 5
AI eases complex medication dosing	“For medication dosing some things got easier… with renal insufficiency you don't have to search long.”	AI support simplifies dose adjustment and preparation, especially for complex cases (e.g., kidney insufficiency, antibiotics).	Interview 5
Lack of interoperability between AI and letter system	“Apennio is not compatible with the program we use for discharge letters.”	AI medication tool is not integrated with the existing letter-writing system, causing workflow friction.	Interview 5
Copy-paste workaround between systems	“We have to copy-paste the medications into the discharge letter.”	Staff manually transfer medication lists between systems due to missing technical integration.	Interview 5
Initial AI training sessions with partial attendance	“There was a training… ten colleagues were on duty, five were there.”	Only part of the team attended the initial AI training due to shift work and scheduling constraints.	Interview 5
Peer-to-peer learning for late joiners	“Later it was: please teach each other.”	Staff who missed training are expected to learn informally from colleagues instead of structured sessions.	Interview 5
Older non-digital-native colleagues struggle with AI	“Colleagues in their fifties… not digital natives… have huge problems with it.”	Older staff experience major difficulties understanding prompts and using the AI tool.	Interview 5
Ongoing ad-hoc support for colleagues' prompts	“You sit there: no, you have to enter it like this… use this prompt.”	The Interview spends time coaching colleagues on how to phrase inputs and interact with the AI.	Interview 5
Vendor dialogue leads to incremental improvements	“There were talks with the company… medication lists were adjusted… things simplified.”	The hospital and ICU discussed issues with the vendor, resulting in some configuration improvements.	Interview 5
AI optimization process is slow and generationally limited	“It's going in the right direction, but it takes time… the 60-year-old colleague might never learn it.”	Improvement takes time, and some senior clinicians may never fully adopt the AI despite simplification.	Interview 5
AI use for letters triggers patient data protection concerns	“ChatGPT wrote underneath ‘influenced by AI’… patients weren't happy their information went to AI.”	When AI attribution remained in discharge letters, patients and families became upset about data being sent to AI.	Interview 5
Difficulty explaining limited AI use (grammar only)	“We had to explain: it was only used to correct grammar, not process private data.”	Staff struggled to reassure patients that AI use was minimal and not substantive clinical processing.	Interview 5
Data protection officer and chief disapprove of careless AI use	“My boss and our data protection officer were not happy about it.”	Leadership and data protection staff react negatively to visible AI references in patient letters.	Interview 5
Human in the loop for medication recommendations	“It gives recommendations… we don't just execute them blindly, we still check.”	AI medication suggestions are treated as advice; clinicians retain decision-making and verification.	Interview 5
AI cannot distinguish clinically irrelevant warnings	“It doesn't distinguish a ninety-year-old from a thirty-year-old woman… always shows pregnancy warnings.”	The AI gives generic warnings (e.g., pregnancy risk) even when clearly irrelevant, revealing lack of contextualization.	Interview 5
Human judgement as irreplaceable safeguard	“Everyone with some common sense knows a ninety-year-old won't be pregnant.”	Clinicians see human judgement as necessary to filter out AI's overcautious or context-blind alerts.	Interview 5
Lack of time for structured team reflection on AI	“It works more on the side… time is too limited to sit down and discuss.”	The team has no dedicated time-outs to reflect on AI use; discussions happen informally.	Interview 5
Email-based collection of staff issues including AI	“I send an email: what problems have you noticed this week? Sometimes these topics come up.”	The Interview gathers problems, including AI-related issues, via periodic email and forwards them.	Interview 5
Strong workload prevents deeper AI engagement	“We are so tightly scheduled… there's no time to deal with it additionally.”	High clinical workload limits the ability to reflect on or optimize AI usage.	Interview 5
Cost savings and digitalization as main AI introduction drivers	“It was mainly a cost-saving measure… cheaper than paper files… digitalisation and documentation duties.”	Management introduced the system primarily for economic and digital documentation reasons.	Interview 5
Staff not involved in tool choice or AI strategy	“They said: now there is this program, please deal with it.”	Clinicians were not consulted on which AI-tool to use or where AI should be applied.	Interview 5
AI system improves shared access vs paper records	“Nurses and doctors can look into the file in parallel… no more fighting over the paper chart.”	Digital system solves prior conflicts over access to a single paper record.	Interview 5
AI documentation enhances traceability of medication errors	“You can better trace… if a wrong administration or non-administration happened.”	Digital AI-supported documentation creates clearer audit trails for medication processes.	Interview 5
Two designated AI contact persons for problem management	“There are two contact persons… one medical and one nursing… for problems and wishes.”	Hospital created roles (from nursing and medical staff) to channel issues and requests to the vendor.	Interview 5
AI contacts focus on problem-solving, not ethics	“They don't really look at ethics like a commission… more problem management.”	These roles handle functionality and usability, not formal ethical oversight.	Interview 5
AI interaction checks require explicit acknowledgement	“Before I can order, I must write: I have taken note of this interaction.”	The system forces users to acknowledge risks (e.g., interactions) before placing medication orders.	Interview 5
System blocks orders if warnings not accepted	“If I click ‘no’ I can't order it that way.”	Technical guardrails prevent ordering medications without formally acknowledging AI-indicated contraindications.	Interview 5
Escalation of questionable AI outputs to liaison staff	“We pass it on to the two women responsible… they must discuss it with the company.”	Clinicians report questionable AI suggestions to the designated contacts, who liaise with the vendor's medical team.	Interview 5
Frontline clinicians not involved in vendor-level resolution	“How it works on that level… we at the front line are not involved.”	Once issues are escalated, clinicians are not integrated in detailed follow-up discussions.	Interview 5
Desire for AI to reduce double documentation in ED	“We have many forms… mostly multiple choice… I'd like KI to transfer this into those forms.”	The neurologist wants AI to auto-fill quality-management and documentation forms from existing ED data.	Interview 5
Documentation burden as major barrier to patient care time	“I sit an extra hour with documentation instead of doing what I was trained for.”	Heavy documentation efforts reduce time available for direct patient care.	Interview 5
IT blocks new AI due to data sensitivity concerns	“Our IT blocked it: these are sensitive data, we can't just throw them into some KI.”	Internal IT rejects further AI documentation solutions citing data protection risks.	Interview 5
No closed internal AI system for documentation support	“We don't have a closed system… just these two programs, no other official KI application.”	Beyond the introduced tools, there is no sanctioned in-house AI environment for broader use cases.	Interview 5
Under-the-table use of public LLMs with anonymised data	“Under the table many of us use Gemini, ChatGPT… with anonymised patient data.”	Clinicians informally use public LLMs for case thinking, anonymising key identifiers.	Interview 5
AI used as research and guideline shortcut	“Forty-year-old man with these complaints… give me the guideline and therapy options.”	LLMs are used to quickly retrieve guideline-based therapies and diagnostics for complex cases.	Interview 5
AI as idea generator and first insight for difficult decisions	“It's like ideas or first insight… to get quickly to the relevant information.”	The neurologist uses AI to shorten the path to relevant literature and options, not to decide.	Interview 5
AI as evidence tool for complex differential diagnoses	“Sometimes decisions are difficult… we look: what did others do, what's evidence-based?”	AI helps identify evidence and comparable cases for challenging therapeutic choices.	Interview 5
Retrospective wish for AI in doctoral research	“I evaluated everything manually… KI could have done this much faster.”	The Interview regrets not having AI tools available during her PhD, which required extensive manual analysis.	Interview 5
Learning programming for research consumed years	“It took two years to write those programs in C++.”	She had to teach herself programming for simulation models, greatly extending research time.	Interview 5
AI could dramatically shorten research cycles	“Six years of research could have been reduced to two.”	AI-assisted coding and analysis could compress lengthy experimental research into much shorter periods.	Interview 5

Concept	Quote	Definition	Interview
Concern about radiologists' job future under AI	"Radiology colleagues… in twenty years… will KI completely take over those jobs?"	She worries that highly image-based specialties might be largely automated by AI.	Interview 5
Neurology perceived as less automatable	"My specialty, neurology, will probably not be hit as much."	Neurology is seen as more reliant on physical examinations and human interaction, harder to automate.	Interview 5
AI as potential necessity due to workforce shortages	"With many colleagues leaving… KI might be needed to maintain high diagnostic accuracy."	AI is framed as a tool to cope with future staff shortages and maintain quality.	Interview 5
Self-education and user-level AI familiarity	"I educated myself in AI and use it as a user, but not deeply in innovation management."	He has proactively learned about AI and uses it personally, without leading AI R&D himself.	Interview 6
SMEs are uncertain, fearful, and myth-driven about AI	"In SMEs there is still a lot of question marks, fear and myth around AI."	Small and mid-sized healthcare firms are described as confused and anxious about AI's implications.	Interview 6
Big Pharma has a very different AI starting point	"If you look at Big Pharma… it's different again than SMEs."	Larger players like Big Pharma operate with more AI experience and infrastructure than smaller firms.	Interview 6
Data-propriety and leakage as dominant AI concern	"A key topic was data… that proprietary data doesn't suddenly go into the big machine."	The main initial worry around AI was losing control of proprietary R&D and know-how to external models.	Interview 6
Need for safe, bounded AI environments ("own garden")	"You can buy your own little garden and be sure the data stays with you."	He stresses the importance of private, walled AI environments where corporate data are contained.	Interview 6
Company-Gemini example of internal AI boundary	"At Company they can feed everything into Gemini… it stays within the companies boundaries."	He contrasts his former SME with Company's internal Google-based AI where data are not used to train global models.	Interview 6
Rapid evolution of enterprise AI offerings	"Two and a half, three years ago this wasn't really possible like now with newer iterations."	Perception that enterprise-grade, data-safe AI options have emerged only in recent model generations.	Interview 6
Regulatory affairs dossier writing as prime AI use case	"For me the best entry use case was Regulatory Affairs… registration dossiers."	He sees regulatory dossier creation as a particularly promising early domain for AI in MedTech/Pharma.	Interview 6
Regulatory dossiers are cumbersome, repetitive and text-heavy	"It's very cumbersome… a lot of tasks, a lot of text writing."	RA work involves extensive repetitive documentation, which he considers well-suited for AI support.	Interview 6
AI can shorten dossier timelines and unlock major value	"If you shorten writing by two, three, four, five months, that's a lot of money."	Time savings in RA dossiers translate directly into earlier market entry and significant financial gains.	Interview 6
RA specialists are scarce; AI should free them for higher-value thinking	"Regulatory Affairs professionals are scarce… better to use them for thinking, not just writing documents."	AI is framed as a way to relieve rare experts from low-value, repetitive documentation work.	Interview 6
Regulatory regimes (MDR vs. 510(k)) add complexity AI can help manage	"MDR for Europe and 510(k) for USA are not identical… AI could be trained for that."	Differing regulatory frameworks increase complexity, which he believes AI could help navigate and translate.	Interview 6
Human revision needed due to hallucinations	"You still need someone to revise it… you can't blindly trust AI because of hallucinations."	He insists that AI-generated regulatory text must be checked by humans for reliability.	Interview 6
Use-case driven AI strategy instead of tool-first	"We wanted to look for use cases… not just say 'we need AI' and pick a tool."	His approach starts from organizational problems and use cases rather than choosing an AI tool first.	Interview 6
Plan to sponsor multiple small AI pilot projects	"We wanted to sponsor a few projects… try this and that, have 2–3 use cases."	Strategy of funding small, exploratory AI pilots to learn and create internal examples.	Interview 6
Selecting open departments and extroverted heads for pilots	"We spoke with department heads who were more extroverted, who said 'I want to try this.'"	Pilots were intentionally placed in units with leaders willing to experiment with AI.	Interview 6
Bottom-up use cases with top-down sponsorship	"We didn't want pure top-down… but also not only bottom-up. We sponsored projects from leadership."	He advocates a hybrid model: leadership support plus bottom-up initiative from interested departments.	Interview 6
Using pilot results to encourage wider adoption	"When a project was finished, we would present it in town halls and department meetings."	Pilot outcomes were meant to be showcased internally to inspire further AI initiatives.	Interview 6
Embedding AI initiatives into managers' objectives	"They wanted it in objectives: at least one AI initiative in your area."	Leadership planned to make AI initiatives part of formal performance goals for managers.	Interview 6
Critique of tool-first, top-down AI implementation	"Some companies say 'AI is cool, we want it'… and squeeze their operations into a tool."	He criticizes organizations that start with an AI tool and then force the organization to fit it.	Interview 6
Tool-first approaches undermine change management and acceptance	"That leads to low acceptance… no proper change management because people weren't involved."	When staff are not included in AI selection and design, adoption suffers.	Interview 6
Company culture of digital and data paranoia	"The company was paranoid… no WiFi… we weren't allowed to use WhatsApp."	His former firm had an extremely cautious culture concerning digital technologies and data leakage.	Interview 6
Need to educate and reassure the board about AI	"We had to regularly tell the board we do this responsibly… data won't leak."	Board members had to be continuously reassured about data safety and pilot design.	Interview 6
Governance as key to data and patient safety	"We must ensure what AI produces is correct; otherwise it can have consequences for patients."	Governance is framed as necessary to prevent patient harm from AI-enabled products and dossiers.	Interview 6
Human in the loop as ethical requirement	"You can't just take everything AI says… you must check because of responsibility to patients."	He echoes a human-in-the-loop logic grounded in clinical and ethical responsibility.	Interview 6
Governance and ethics must be communicated to entire workforce	"Important to communicate openly about governance and ethics with the whole workforce, not only part."	Responsible AI requires broad internal communication, not only selective audiences.	Interview 6
Risk of employees using unapproved AI tools with confidential data	"One might use DeepSeek, another Perplexity… what you put in there feeds the big model."	He worries that staff will use unsanctioned AI tools and inadvertently leak confidential information.	Interview 6
Need for clear corporate AI provider agreements	"If we have a deal with Gemini or ChatGPT, what you put in others will go into their model."	Organizations must define which AI providers are approved and explain consequences of using others.	Interview 6
Healthcare boards are older and conservative about AI	"Boards in healthcare are usually 60+ and further away from AI."	He portrays healthcare boards as older, risk-averse, and less familiar with digital technologies.	Interview 6
Necessity of bringing the board along to secure investment	"If they don't understand it, they might block… which harms competitiveness."	AI progress depends on educating boards so they approve necessary investments.	Interview 6
Suggestion for CEO-level AI budget and ownership	"I'd put it at the CEO level… ring-fence a budget for projects."	He recommends locating AI responsibility and budget with the CEO to signal strategic importance.	Interview 6
AI benefits still uncertain but require experimentation	"The benefit isn't always clear yet… we need to experiment with pilot projects."	Despite unclear ROI, he argues for experimentation to learn how AI can create value.	Interview 6
Learning by doing, failing and "failing fast"	"We must learn by doing and by failing… 'failing fast,' the classic words."	He endorses an experimental mindset where failures are accepted as part of AI learning.	Interview 6
Warning that overly conservative firms risk obsolescence	"If the company is too conservative… we risk becoming obsolete."	He warns that avoiding AI experimentation can cause loss of competitiveness and relevance.	Interview 6
Analogy between AI today and the early internet era	"It's comparable to the internet 20 years ago… you can't just say 'this won't be anything.'"	AI is likened to the early internet: initially unclear value, but impossible to ignore long term.	Interview 6
Leadership belief in AI combined with bottom-up enthusiasm	"It needs leadership that believes we need it, then we take people with affinity for pilot projects."	Effective AI adoption requires leaders who push, plus volunteers with interest and affinity.	Interview 6
Risk of uncontrolled bottom-up AI without leadership framework	"If it isn't organized from above, people might start on their own and build a huge black box."	He cautions that purely bottom-up AI initiatives without governance can create opaque, risky systems.	Interview 6
Snowball effect of successful AI pilots inside the firm	"Others see 'this saved that much' and say, can I talk to them… snowball effect."	Successful pilots are expected to trigger interest and imitation across departments.	Interview 6
Research–bedside gap in robotics and AI	"In 2021 a lot was researched and tried, but nothing was at the bedside."	Perception that robotics/AI remain largely in research and have not reached routine clinical practice.	Interview 7
Low digital and AI literacy among experienced nurses	"Participants have almost no connection… we start from scratch: this is a computer."	Many continuing-education participants lack basic familiarity with digital technologies and AI concepts.	Interview 7
Respect, uncertainty and time concerns around robotics	"There is high respect, much uncertainty… they say it all takes too much time."	Staff perceive robotic systems (e.g. Da Vinci) as intimidating, error-prone and slower than conventional methods.	Interview 7
Physicians teach robotics, educators take AI topics	"Doctors usually teach robotics and we now take AI for assessments."	Division of labour where medical staff cover robotics and nurse educators begin integrating AI into coursework.	Interview 7
Self-developed AI assessment criteria for student work	"We are just starting to build our own system to grade work with AI."	Educators design evaluation frameworks for AI-supported assignments because institutional guidance is absent.	Interview 7
Learners' fear and lack of confidence using AI tools	"There is still a big 'oh, I don't know how that works' among participants."	Many learners are hesitant and insecure about using AI, requiring basic orientation.	Interview 7
Need for holistic acceptance "head, heart, body"	"It has to go into the head, heart and body… acceptance must be holistic."	AI must become fully accepted cognitively, emotionally and practically to be used naturally.	Interview 7
Everyday-technology analogies to build trust	"I don't run beside my car checking the digital speedometer."	The educator uses analogies (cars, toothbrush) to normalise trust in digital systems.	Interview 7
Humans can fail too, not only machines	"Trust in us humans is also limited… we can fail as well."	Emphasising that both human staff and machines are fallible, challenging one-sided mistrust of technology.	Interview 7
Regulatory and curricular vacuum on AI in education	"There is practically nothing specified… we develop the curriculum ourselves."	Lack of clear legal or curricular guidance on how AI should be integrated into nursing education.	Interview 7
Pending state curriculum mandating digital & AI content	"The new curriculum from the ministry should cover digital work and AI, maybe from 2027."	Anticipated future curriculum requiring AI topics, but timing and content remain uncertain.	Interview 7
Reliance on external experts for AI competence	"We need experts who come and teach us… different perspectives."	Educators see the need for external specialists to provide deeper AI expertise and training.	Interview 7
Ethics seen as crucial but under-addressed for AI	"Ethical aspects are super important but not really tackled yet."	Recognition that ethical issues of AI are central but insufficiently treated in practice.	Interview 7
Ethics and legislation lag behind AI implementation	"The framework always comes later in Germany… ethical principles and legislation are missing."	View that ethical and legal frameworks are developed only after technologies cause problems.	Interview 7

Concept	Quote	Definition	Interview
Data protection and compliance as practical gatekeepers	"Data protection and compliance departments look very closely at what is allowed."	Operational governance around AI currently centres on data protection and compliance departments.	Interview 7
Limited structured reflection spaces for AI	"We create days for exchange, but AI is only a small part."	There are emerging but limited formal spaces to discuss AI in practice and education.	Interview 7
One-off trainings with learning-by-doing afterwards	"It is trained once… the rest you somehow have to manage yourself."	New tools are introduced via single training sessions followed by informal learning in daily work.	Interview 7
Misalignment between education and practice timelines	"It's slowly integrated in generalist training, but in practice it's still an unborn child."	Education starts addressing AI while many practical settings still lack implementations, creating a temporal gap.	Interview 7
Perceived international lag and half-measures in Germany	"In Denmark or Sweden things are decided and organised together… here it's always half things."	The educator contrasts proactive Nordic approaches with Germany's reactive, fragmented handling of AI.	Interview 7
Top-down technology procurement without co-design	"It's top-down… things are bought and we are told: learn this now."	AI and digital tools are selected centrally and introduced without involving future users in design.	Interview 7
Limited involvement of frontline staff in vendor selection	"Products are tested by a few people… then suddenly it's there."	Only small groups participate in trials before hospital-wide roll-out, reducing broad input.	Interview 7
Persistence of poorly applicable tools in practice	"Even if later we see it's not applicable in practice, then we just have it."	Once implemented, tools tend to remain even when misaligned with clinical realities.	Interview 7
Private, governance-free experimentation with "shadow AI"	"That's how I work… in my private space, to develop things for school."	The educator uses AI privately outside institutional governance, matching the notion of "shadow AI".	Interview 7
Quality management leads external communication on AI	"Quality management publishes information about it through the hospital channels."	QMS units coordinate public communication about new digital/AI tools.	Interview 7
Transparency towards patients about AI and robotics	"Patients know whether they are operated on by a computer or by hands."	The organisation informs patients about technology use, partly as ethics and partly as marketing.	Interview 7
Ethical aspects considered in patient-facing communication	"All ethical aspects are considered so there is no disaster."	Ethical considerations shape how AI and robotics are communicated to patients.	Interview 7
Absence of dedicated AI roles or structures	"There are no roles only for this… we are not that far yet."	No specific AI governance or expert roles exist in the educator's environment.	Interview 7
Educators act as translators of legislation into curricula	"Our management is the legislation… we translate it and implement it."	The school interprets legal requirements and turns them into educational content and practice.	Interview 7
Desire for external coaching and working groups	"It would be great if the state provided coaches and working groups."	Wish for state-supported experts and cross-hospital working groups to develop AI approaches.	Interview 7
Quality management monitors tools over time	"For the hospital, quality management tracks this over time and looks closely."	QMS monitors ongoing use and evolution of new tools, including AI.	Interview 7
Education must incorporate lessons learned from practice	"We have no choice but to take new things up and teach them."	The school continuously integrates practical experiences with AI into its teaching.	Interview 7
Vendor-provided initial trainings with sign-off	"Everyone must go through the training and sign that they learned it."	Tool vendors deliver initial courses that staff must attend and formally acknowledge.	Interview 7
Demographic staff shortages limit training capacity	"Demographic change hits… we are simply too few."	A shrinking workforce reduces capacity for extensive AI training and governance.	Interview 7
High potential of AI and robotics at bedside	"The greatest potential is directly in nursing at the bedside."	The educator sees strongest AI/robotics benefits in direct patient care, especially in intensive care.	Interview 7
Assistive technologies for communication with intubated patients	"There are tools where intubated patients can contact a computer."	Technologies enabling communication and interaction for ventilated, non-speaking patients are highlighted.	Interview 7
Staff relief rather than staff saving as AI goal	"It's not about saving staff… we don't have any to save."	AI should relieve existing staff, not cut positions, given current shortages.	Interview 7
Acute staffing crisis due to late technology adoption	"If we had introduced these things ten years ago, staff wouldn't be so exhausted."	Delayed adoption has contributed to current extreme burden and burnout among caregivers.	Interview 7
Workload makes acceptance-building doubly difficult	"Creating acceptance now in this nursing shortage is twice as hard."	High pressure in care work constrains capacity to engage with and accept AI tools.	Interview 7
Political resistance to migration constrains staffing	"Many people are against getting support from other countries."	Anti-immigration attitudes reduce the feasibility of addressing shortages via foreign staff.	Interview 7
Systemic missteps leading to structural lag	"In the eighties we took the wrong turn and stopped keeping up."	The educator frames Germany's current lag as a result of decades of missed opportunities.	Interview 7
AI adoption as necessary to prevent system collapse	"We won't get support from humans anymore… we need this support from AI."	AI is portrayed as essential to maintain care quality amid demographic and workforce trends.	Interview 7
Rising patient age and acuity increase pressure	"Patients become older and sicker… they all have to be cared for."	Ageing, multi-morbid patient populations intensify workload and the need for technological support.	Interview 7
Relationship-based pedagogy to build AI trust	"I work with relationship didactics… build trust with each person."	The educator emphasises relational, trust-based teaching to introduce AI to staff and learners.	Interview 7
Need for protected time windows for AI learning	"We must create time windows so people can learn and experience it."	Effective AI adoption requires dedicated time for exploration and guided practice, not only ad hoc use.	Interview 7
No AI tools yet implemented in the practice	"No tool has been implemented so far."	The radiology practice has discussed AI but has not introduced active tools.	Interview 8
Industry regularly offers AI solutions	"There are offers from industry."	Vendors frequently approach the practice with AI propositions.	Interview 8
AI solutions perceived as too expensive	"Usually it's too expensive… they want payment per case."	Costs, especially per-case pricing, are the main barrier to AI adoption.	Interview 8
No universal radiology AI; only narrow tools	"There is no universal tool that can do everything."	AI applications in radiology are highly specialized, limiting broad adoption.	Interview 8
AI helpful for specific quantitative tasks	"The AI calculates all angles for leg-axis imaging."	Certain AI tools provide strong support for measurement-heavy diagnostic tasks.	Interview 8
AI as third reader in mammography not reimbursed	"As third-reader in mammography— not reimbursed by insurers."	Lack of reimbursement prevents routine AI use in mammography.	Interview 8
Patients resist paying extra for AI	"Hard to explain patients must pay extra for better AI reading."	Financial co-payment reduces patient acceptance.	Interview 8
Scanner-integrated AI improves quality & speed	"New scanner software uses AI… better images, shorter scan times."	AI embedded in imaging hardware enhances efficiency and reduces dose.	Interview 8
Purchased AI "acceleration modules" are valuable	"Colleagues bought AI acceleration… it's worth the money."	Add-on AI modules for scanners deliver tangible performance benefits.	Interview 8
AI supports literature retrieval for rare findings	"AI shows papers immediately instead of long searching."	AI accelerates retrieval of relevant scientific articles for unusual findings.	Interview 8
AI adoption driven by workforce shortages	"Due to personnel shortage… development will go there."	Staffing constraints push radiology toward AI augmentation.	Interview 8
Need for human oversight ("human in the loop")	"AI must always be supervised by humans."	The Interview insists on maintaining human verification over AI outputs.	Interview 8
AI requires narrow, domain-specific training	"AIs are trained very specifically; cannot do everything."	AI must be specialized for narrow tasks to perform reliably.	Interview 8
High acceptance among radiologists if affordable	"Acceptance is there… if cost-benefit works."	Clinicians are open to AI if economically viable.	Interview 8
AI can act as pre-reader for large image volumes	"If AI pre-reads and flags what you can release…"	Radiologists welcome AI support to handle increasing imaging workloads.	Interview 8
AI valuable for staging & volumetry	"KI measuring tumor progression would save much work."	Automated volumetric measurements are seen as especially beneficial.	Interview 8
Lack of reimbursement for AI limits implementation	"There is no billing code for running AI."	Missing compensation models hinder adoption despite clinical value.	Interview 8
Radiologists privately experiment with AI LLMs	"I used ChatGPT privately to describe findings."	Clinicians use public LLMs informally for differential diagnoses.	Interview 8
AI-enabled differentials can outperform manual search	"It gave a perfect differential diagnosis."	AI sometimes provides diagnostic suggestions superior to literature searches.	Interview 8
AI-supported resources may be embedded in paid tools	"No idea if they use AI or keywording."	Diagnostic search tools may or may not use AI; users cannot tell.	Interview 8
Ethical duty to use AI if evidence supports it	"Ethically wrong to withhold AI if it is better."	Ethical stance: proven AI should be used to improve care.	Interview 8
Necessity of human plausibility checks	"Machines miss rare things; humans must check."	AI cannot detect rare or atypical patterns reliably.	Interview 8
Explosion of imaging data requires AI	"From 80 images to 1000 per exam… must process all."	Increasing scan volumes make manual review burdensome.	Interview 8
Lung cancer screening requires AI by regulation	"AI is required for lung cancer screening."	New screening programmes mandate AI involvement.	Interview 8
Automated volumetry mandated in screening	"AI must calculate tumor growth; I may not do it manually."	Regulation requires AI for specific measurement tasks.	Interview 8
Quality and accuracy of AI expected to improve	"It's a matter of time until it gets better."	Skepticism about current quality but optimism for future accuracy.	Interview 8

Concept	Quote	Definition	Interview
Limited inter-practice knowledge sharing	“No fixed forum; colleagues don't show their cards.”	Competitive dynamics reduce cross-practice collaboration on AI.	Interview 8
German Radiological Society offers AI training	“They offer certificates to teach basics of AI.”	Professional bodies are beginning to provide formal AI education.	Interview 8
Internal discussions drive AI learning	“Always internal… never with competitors.”	AI knowledge exchange occurs only within the organization.	Interview 8
AI helpful for phone & appointment management	“Telephone and scheduling, AI could help a lot.”	Administrative processes seen as promising AI applications.	Interview 8
Possible AI use for inventory & procurement	“AI could help know when to reorder materials.”	Procurement and stock management viewed as potential AI use-cases.	Interview 8
Scheduling already semi-automated but needs oversight	“Planning software works, but humans must check.”	Existing digital systems require human review for fairness and correctness.	Interview 8
Manual review of documentation is labour-intensive	“We might need to employ five nurses full time just to read the faxed notes.”	Incoming clinical documentation would require substantial human effort without automation.	Interview 9
NLP demo as triggering event for AI conviction	“He showed me the technology… that was the triggering event for me.”	Seeing an NLP system read reports and surface insights convinced him of AI's feasibility.	Interview 9
AI replaces repetitive data-extraction labour	“I don't need five human beings… I can have a digital system extracting data.”	AI is framed as a substitute for manual extraction of information from records.	Interview 9
Cloud processing raises primary privacy concerns	“First point of issue is privacy… you're sending sensitive health information to the cloud.”	Moving health data to external cloud environments is seen as the first regulatory/ethical hurdle.	Interview 9
Highly sensitive clinical content intensifies risk	“You're sending information… about mental health, about their cancer, about their health problems.”	The depth and sensitivity of clinical content create additional layers of regulatory concern.	Interview 9
Third-party data processing complicates responsibility	“I have clinic software… I'm sending the data to somebody else… processing it through somebody else.”	Using external AI vendors introduces extra questions about consent, control, and accountability.	Interview 9
Different jurisdictions impose different consent regimes	“In the UK and in the EU, GDPR is a little tougher.”	Regulatory expectations for AI data use vary across Canada, US, UK, and EU.	Interview 9
Insight as distinct and valuable asset	“The insight is the true value and the insight is generated by a third party.”	Distinguishes raw data from AI-generated insights, treating insights as a separate value layer.	Interview 9
Unclear ownership of model-enriched data	“If we build new models on old data, who should be getting the rights?”	Raises unresolved questions about who owns enriched or model-derived information.	Interview 9
Anticipated market for stakeholder-management specialists	“Maybe third party companies… managing your stakeholders and your data ownership.”	Predicts new firms that specialise in managing AI-related stakeholder and data-ownership issues.	Interview 9
Internal governance focuses on data handling basics	“How do we save our data, how long do we save our data, how we delete it?”	Describes internal governance around storage, retention, deletion and data-sharing policies.	Interview 9
Intelligent systems increasingly govern themselves	“Now you have intelligent systems governing themselves.”	Notes a shift toward AI systems that monitor and update other AI components.	Interview 9
Gold standard shifting from human to software	“Over time the gold standard is shifting back to software.”	As models improve, software performance becomes the reference instead of human performance.	Interview 9
Self-updating algorithms challenge legal accountability	“The software was updating itself or modifying itself… outside the control of the human team.”	Self-modifying algorithms complicate explanations of how particular decisions were produced.	Interview 9
Humans only partially "in the loop"	“Humans are in the loop of the algorithm and not at the level of the data.”	Human oversight occurs at an abstract algorithm level, not over the full underlying data stream.	Interview 9
Audit scope must match data and model dynamics	“Link your audit to every algorithm when it's updated or evolved.”	Suggests audits triggered by model updates or data volume rather than calendar cycles.	Interview 9
AI work ultimately impacts patient healthcare	“At the end of the line… there is patient healthcare.”	Frames all AI data and analytics work as ultimately affecting patient care.	Interview 9
Personal lens focused on frontline care	“I have a lens that focuses on the frontline care.”	The Interview prioritises AI projects that influence direct patient care processes.	Interview 9
Selective involvement based on patient benefit	“I involve myself… if I think it would have a positive impact on patient care.”	Uses expected patient benefit as a criterion for engaging with particular AI ventures.	Interview 9
Founders face tension between ideals and survival	“When you're struggling as a founder you have to take contracts… paying your employees.”	Acknowledges conflict between moral aspirations and commercial survival pressures in AI startups.	Interview 9
Extraction and transformation as core AI value	“Extraction and transformation are where all the value is.”	Defines AI's main function as extracting information and transforming it into decision-ready outputs.	Interview 9
AI expected to replace processing labour	“It's gonna eliminate labour… involved in processing images and saying what was being tagged.”	Predicts job displacement in routine data-processing and annotation tasks.	Interview 9
Natural language to code as emerging capability	“Going from natural language to code… it's getting there.”	Highlights progress in AI that converts textual instructions into executable code.	Interview 9
Future semantic understanding of nuanced language	“We'll see better understanding by AI systems of what we're saying as humans.”	Anticipates deeper semantic comprehension and nuance handling by AI.	Interview 9
Improved translation across human and technical "languages"	“We'll see better translation… machine language, economic language, personal language.”	Envisions AI translating not only human languages but also domain-specific languages.	Interview 9
Machine vision converts images to diagnoses	“I'm going to look at an X-ray, turn it into a diagnosis.”	Describes AI turning visual data (e.g., X-rays) into diagnostic concepts.	Interview 9
Analysis shifting from humans to machine systems	“We're gonna see a lot of that analysis go away from humans and go to machine systems.”	Predicts machines will assume many analytic tasks historically performed by clinicians.	Interview 9
Humans retain comparative advantage in creativity	“Humans will still always be better at creative matters and… abstract thinking.”	Argues human superiority will remain in high-level abstraction and novel theorising.	Interview 9
Traditional analogue care model at breaking point	“We're at a breaking point with the old model of healthcare.”	Claims current doctor-centric, serial care delivery can no longer scale to global needs.	Interview 9
AI enables parallel processing and digital assistants	“We'll have parallel processing… multiple digital minds, digital assistants.”	Sees AI as enabling many concurrent "digital minds"supporting clinicians.	Interview 9
Generational transition in physician mindset	“Old physicians are going to retire with the old legacy system of thinking.”	Presents the shift to AI-enabled care as linked to generational change in the profession.	Interview 9
Analogy between AI era and early internet	“No different than when physicians first got the internet.”	Compares current AI transformation to the earlier introduction of internet access in medicine.	Interview 9
Vision of massively expanded physician panel size	“One physician can probably take care of 100,000 patients rather than only 2000.”	Suggests AI could let one physician manage far larger patient populations.	Interview 9
Global access to "smartest mind" via ubiquitous AI	“Anybody on the planet could eventually have access to the smartest mind about their health.”	Envisions AI democratising expert-level health insight worldwide.	Interview 9
Expectation of hype–correction cycle for AI	“Everything is going to look cool… then broken… then shocking… like the internet.”	Anticipates cyclical phases of hype, disillusionment, and stabilisation in AI adoption.	Interview 9
Uses speech-recognition tool for dictation	“We have a speech-recognition program… it writes the letters.”	Uses digital dictation; not sure whether to classify it as AI.	Interview 10
Rejects passive audio recording tools	“We don't have anyone secretly listening; others do that.”	Opposes continuous, automatic recording of patient conversations.	Interview 10
Receives AI vendor outreach via email or mail	“I get mails or letters sometimes… no calls.”	Vendors contact him to promote AI-based tools.	Interview 10
Sees DoctorLib-style assistants as inevitable	“On the long run you can't avoid things like DoctorLipp.”	Predicts necessity of workflow automation due to staffing shortages.	Interview 10
Telephone shortages drive AI scheduling	“You can't get enough people for the phone… need an assistant.”	Limited administrative staff pushes AI-based front-desk automation.	Interview 10
Does not want AI recording and transcribing consults	“I don't see it for us… someone recording talks.”	Rejects ambient scribing for ethical/privacy reasons.	Interview 10
Open to complex-case AI assistance	“If it's very differentiated… you could let a AI run over it.”	Sees value in using AI for rare, complex ECG/chemotherapy-related cases.	Interview 10
Routine ECG holds little AI benefit	“I see no benefit for me in routine.”	For simple diagnostics, human workflow already efficient.	Interview 10
AI will come strongly in ultrasound	“Ultrasound findings will be AI-analysed… I'm quite sure.”	Predicts major adoption of AI in ultrasonography.	Interview 10
Radiology will be massively automated	“In X-ray reporting it will be massive.”	Expects high automation rates in radiological image interpretation.	Interview 10
AI superior when trained on millions of images	“Millions of findings behind it… better than freehand ultrasound.”	Argues performance advantage when AI leverages large training datasets.	Interview 10
Unsure whether AI can replace physicians	“I cannot judge whether a AI can replace humans.”	Expresses uncertainty toward full clinical replacement.	Interview 10
Belief that AI will replace radiologists	“We agree AI will replace radiologists.”	Predicts displacement of radiologist labour.	Interview 10
Human will remain for serious-case conversations	“One will be there for bad findings, to moderate.”	Envisions residual human role in emotionally sensitive communication.	Interview 10
Normal X-rays will no longer be reviewed by humans	“Routine chest X-rays… no one will look at them anymore.”	Foresees full automation for low-risk imaging.	Interview 10

Concept	Quote	Definition	Interview
Data always accessible to someone	“There's always someone who manages to access data.”	Skeptical about security; believes breaches inevitable.	Interview 10
Continuous attempts to breach data	“People try until they accessed the data.”	Highlights persistence of attackers as risk.	Interview 10
Low-security firewalls in GP practices	“GP practice firewalls are not good.”	Notes that vulnerable infrastructure enables data leaks.	Interview 10
Sensitive mental-health data risk severe consequences	“If depression data leaks… massive implications for career.”	Concern about stigma and financial discrimination from breaches.	Interview 10
Transparency of structured diagnosis data is high	“Diagnosis codes make data very transparent.”	ICD-coding systems facilitate rapid identification of patient cohorts.	Interview 10
Data easier to access than paper records	“Nobody breaks into a GP office for paper records.”	Compares digital vulnerability to physical security.	Interview 10
Data-mining yields sensitive insights	“Search engine over stolen data… you get depression rates.”	Highlights ease of extracting patterns from stolen datasets.	Interview 10
AI will further simplify data access	“Data will be even easier to get with AI.”	Expects AI to accelerate misuse risks.	Interview 10
AI will revolutionise healthcare	“It will get a huge importance.”	Views AI as a major future driver of medical change.	Interview 10
Fear that physicians could "abolish themselves"	“We must be careful not to abolish ourselves.”	Concern that overly automating tasks risks making physicians redundant.	Interview 10
Radiology demand will collapse	“Radiology will have a huge collapse in need for doctors.”	Predicts drastic reduction in radiologists due to automation.	Interview 10
Physician self-reflection needed to stay relevant	“You must question how you see yourself as a doctor.”	Suggests adapting professional identity to avoid redundancy.	Interview 10
Low-effort physicians more replaceable	“If six-hour day is enough… don't wonder if replaced by AI.”	Suggests complacency accelerates automation risk.	Interview 10
Manual, invasive specialties less replaceable	“Manual work like catheterisation is less replaceable.”	Differentiates between replaceable cognitive tasks and invasive tasks.	Interview 10
Dermatology and radiology highly replaceable	“Dermatologists… radiologists may not be needed.”	Views image-based specialties as vulnerable.	Interview 10
GP becomes central coordinator of AI-enabled care	“The GP will benefit extremely… gets the specialist report.”	Predicts strengthening of primary care vian AI-generated specialist-level outputs.	Interview 10
AI transforms diagnostic pathways	“Everything non-invasive will more or less disappear.”	Predicts structural change in diagnostic services due to automation.	Interview 10
No current AI usage in the practice	“We currently have no touchpoints.”	States that the practice does not yet employ AI-based tools.	Interview 11
AI could support ECG and BP analysis	“AI-controlled long-term ECG or BP analysis could help us.”	Sees potential in automated interpretation of cardiology diagnostics.	Interview 11
Cost concerns as barrier to AI adoption	“It's of course a cost question.”	AI tools are perceived as financially difficult to justify.	Interview 11
No revenue benefit expected from AI	“We don't know how AI would increase our revenue.”	AI adoption is not seen as economically beneficial in the current setup.	Interview 11
High workload reduces motivation to adopt AI	“We are completely at capacity… no need for AI now.”	Current patient volume and workflow efficiency reduce incentives to introduce new tools.	Interview 11
AI may become relevant with new practice expansion	“This may change when we open a new practice.”	Future structural changes could make AI adoption more attractive.	Interview 11
No current need for faster report generation	“Our structured approach is very fast… no pain point.”	Manual reporting is already efficient; no urgency to automate.	Interview 11
AI could help filter artefacts in long-term ECG	“AI can certainly filter artefacts in long-term ECGs.”	Identifies a concrete diagnostic use-case where AI could reduce noise.	Interview 11
AI will automate routine radiology findings	“Normal X-ray findings will go automatically.”	Predicts automation of simple imaging assessments.	Interview 11
Patients will receive AI-driven automated reports	“Patients will be directly informed on their phones.”	Envisions automated delivery of diagnostic results to patients.	Interview 11
Remote device monitoring vian AI already emerging	“Pacemaker patients already have iPads to read data.”	Notes existing telemonitoring technologies as early AI-enabled examples.	Interview 11
Strong ethical concerns about data hacking	“If someone hacks medical data, the consequences are gigantic.”	Expresses severe concern about data breaches and their real-world effects.	Interview 11
Medical data misuse could harm access to credit/insur-ance	“If insurers learn your risk factors, you might not get a loan.”	Warns of financial discrimination when sensitive health data is exposed.	Interview 11
Cloud storage increases vulnerability	“Cloud storage is a major issue.”	Sees cloud-based AI tools as particularly exposed to hacking.	Interview 11
Data retrieval via ICD codes makes misuse easier	“You can search ICD codes and get 80,000 patients in seconds.”	Points out how structured coding systems enable rapid data extraction.	Interview 11
AI will make data access even easier	“With AI, data access will be even easier.”	Predicts that AI will accelerate the speed and scale of data misuse.	Interview 11
New practice will integrate AI-enabled systems	“We have a new telephone system that is surely AI-based.”	New infrastructural systems are expected to include AI components.	Interview 11
Will adopt AI modules if offered with new systems	“They will tell us which AI tools we can book.”	Open to integrating AI extensions provided by system vendors.	Interview 11
EKG analysis system likely already AI-supported	“Our new ECG evaluation is likely AI-supported.”	Believes diagnostic software upgrades already embed AI functionalities.	Interview 11
AI as a major future driver in medicine	“AI will get a very big importance in medicine.”	Foresees significant long-term impact of AI on medical practice.	Interview 11
AI improves diagnostic accuracy through large datasets	“With 50 million skin cancer images, AI has higher hit rates.”	Highlights scale-driven advantage of AI in dermatology and oncology.	Interview 11
AI will revolutionize diagnostic practice	“I think it will revolutionize things.”	Predicts transformational change in clinical diagnostics.	Interview 11
Uncertainty whether current AI hype is justified	“Not sure if it will be the hype the stock market predicts.”	Questions speculative expectations around AI.	Interview 11
Manual, invasive procedures less replaceable	“Manual work like catheterization is less replaceable.”	Distinguishes between replaceable diagnostic tasks and less automatable manual ones.	Interview 11
Non-invasive specialties more vulnerable to automation	“Everything non-invasive will more or less disappear.”	Predicts substantial automation of non-invasive medical fields.	Interview 11
Dermatology and radiology particularly vulnerable	“Dermatologists and radiologists may no longer be needed.”	Foresees displacement in image-based specialties.	Interview 11
AI will generate specialist-level findings for GPs	“The GP will get the specialist report directly.”	Envisions AI shifting specialist knowledge to primary care.	Interview 11
House physicians become central coordinators	“The GP will certainly benefit extremely.”	Predicts structural strengthening of general practice.	Interview 11
Surgical robotics show high precision	“Robots like Da Vinci are already very good.”	Notes success and precision of robotic-assisted surgery.	Interview 11
AI robotics still require human oversight	“There must still be someone doing it.”	Emphasises continued necessity of human operators despite automation.	Interview 11
Physician-led AI governance role	“Founder & Executive Lead of… physician-led medical AI.”	The Interview positions themselves as clinically accountable leader of AI initiatives.	Interview 12
Strategic oversight of AI projects	“My role includes strategic oversight of AI projects.”	Responsibility for setting direction and priorities of AI development and deployment.	Interview 12
Clinical quality assurance responsibility	“Clinical quality assurance.”	Ensuring AI systems meet clinical safety and quality standards.	Interview 12
Governance design as core task	“Governance design.”	Active involvement in creating governance structures for AI use.	Interview 12
Coordination of international pilot sites	“Coordination of multi-country pilot sites.”	Managing geographically distributed clinical validation environments.	Interview 12
Structural clinical challenges drive AI adoption	“Structural clinical challenges… accelerated adoption.”	AI work is triggered by systemic pressures in healthcare delivery.	Interview 12
Rising complexity motivates AI use	“Rising complexity.”	Increasing medical and organizational complexity necessitates AI support.	Interview 12
Resource constraints as adoption driver	“Resource constraints.”	Limited human or financial resources motivate AI exploration.	Interview 12
Lack of clinically grounded AI as problem	“Lack of clinically grounded AI.”	Existing AI solutions are perceived as insufficiently clinical.	Interview 12
Regulatory pressure accelerates adoption	“Regulatory pressure… accelerated adoption.”	External regulation acts as catalyst rather than barrier.	Interview 12
EU AI Act as key external influence	“EU AI Act.”	European AI regulation shapes design and governance choices.	Interview 12

Concept	Quote	Definition	Interview
GDPR shapes AI development	"GDPR."	Data protection regulation constrains data use and system design.	Interview 12
Accreditation requirements influence AI	"Clinical accreditation requirements."	Formal clinical standards affect AI adoption.	Interview 12
International partners shape expectations	"International partner expectations."	External collaborators influence responsible AI practices.	Interview 12
Global Responsible AI trend	"Global trends toward Responsible AI."	Broader societal and professional discourse affects AI strategy.	Interview 12
Clinical leadership enables AI adoption	"Clinical leadership."	Strong clinical leadership is seen as prerequisite for responsible AI.	Interview 12
Digital maturity as internal enabler	"Digital maturity."	Organizational readiness supports AI implementation.	Interview 12
Interdisciplinary teams support AI	"Interdisciplinary teams."	Collaboration across professions enables AI development.	Interview 12
Strong safety culture	"Strong safety culture."	Organizational norms prioritize patient safety in AI work.	Interview 12
Pilot hubs enable structured experimentation	"International pilot hubs."	Controlled environments are used to test AI safely.	Interview 12
Patient safety takes precedence	"Patient safety… take precedence."	Safety is the primary decision criterion in conflicts.	Interview 12
Regulatory compliance prioritized over innovation	"Regulatory compliance take precedence."	Innovation is subordinated to legal and regulatory requirements.	Interview 12
Cross-functional evaluation of conflicts	"Cross-functional evaluation."	Conflicts are resolved through interdisciplinary review.	Interview 12
Temporary project halting when risk unclear	"Temporary halting of projects."	Willingness to pause AI initiatives under uncertainty.	Interview 12
Early consideration of ethical risks	"Ethical… risks are addressed early."	Responsibility is integrated at early stages of AI work.	Interview 12
Societal risks considered in AI	"Societal risks."	Broader societal implications are explicitly acknowledged.	Interview 12
Joint physician–technical evaluation	"Physicians and technical teams jointly evaluate."	Responsibility is shared across professional groups.	Interview 12
Documentation of responsibility decisions	"Document decisions."	Formal documentation supports accountability.	Interview 12
Structured impact assessment	"Structured impact assessment."	Systematic methods are used to anticipate impacts.	Interview 12
Scenario testing before deployment	"Scenario testing."	Hypothetical futures are explored prior to implementation.	Interview 12
Risk identification as formal practice	"Risk identification."	Risks are explicitly mapped and assessed.	Interview 12
Stakeholder mapping	"Stakeholder mapping."	Identification of affected groups precedes deployment.	Interview 12
Early validation in pilot hubs	"Early validation in pilot hubs."	Clinical testing occurs before scaling.	Interview 12
Reflection built into AI lifecycle	"Reflection points are built into the lifecycle."	Reflexivity is institutionalized across stages.	Interview 12
Pre-development reflection	"Pre-development."	Assumptions are challenged before building systems.	Interview 12
Mid-iteration reflection	"Mid-iteration."	Ongoing reassessment during development.	Interview 12
Pre- and post-deployment review	"Pre-deployment and post-deployment reviews."	Continuous reflection after technical completion.	Interview 12
Broad stakeholder involvement	"Clinicians, nurses, patients, tech teams."	Multiple stakeholder groups shape AI decisions.	Interview 12
Governance bodies involved	"Governance bodies."	Formal oversight actors participate in decision-making.	Interview 12
Transparency as daily design principle	"Transparency."	Openness guides everyday AI-related work.	Interview 12
Explainability as requirement	"Explainability."	Models must be interpretable to users and stakeholders.	Interview 12
Guardrails embedded in models	"Guardrails."	Technical and organizational limits constrain AI behavior.	Interview 12
Monitoring influences daily decisions	"Monitoring influence all decisions."	Continuous oversight affects routine operations.	Interview 12
Three-layer decision model	"Three-layer model."	Decision-making is structured across multiple governance levels.	Interview 12
Clinical leadership layer	"Clinical leadership."	Clinical authority forms one governance layer.	Interview 12
Technical governance layer	"Technical governance."	Technical oversight is institutionally separated.	Interview 12
Executive steering layer	"Executive steering."	Strategic decisions occur at executive level.	Interview 12
Clinical & Scientific Board oversight	"Clinical & Scientific Board."	Formal boards provide expert oversight.	Interview 12
Model owners assigned	"Model owners."	Clear accountability for individual AI models.	Interview 12
Risk frameworks guide oversight	"Risk frameworks."	Formalized tools structure risk governance.	Interview 12
Working groups support governance	"Working groups."	Specialized teams handle AI-related tasks.	Interview 12
Lifecycle documentation maintained	"Lifecycle documentation."	Documentation spans development to deployment.	Interview 12
Drift monitoring	"Drift monitoring."	Performance changes over time are tracked.	Interview 12
Audits as routine practice	"Audits."	Formal checks ensure compliance and quality.	Interview 12
Clinical validation required	"Clinical validation."	AI systems must demonstrate clinical effectiveness.	Interview 12
Automated risk triggers	"Automated risk triggers."	Technical mechanisms flag emerging risks.	Interview 12
Principle-based escalation	"Escalation follows defined principles."	Difficult decisions follow predefined rules.	Interview 12
Long-term impact considered	"Long-term impact."	Decisions account for future consequences.	Interview 12
Innovation value balanced with safety	"Innovation value."	Innovation is weighed against safety and compliance.	Interview 12
AI enhances training	"AI enhances training."	AI contributes to professional development.	Interview 12
AI improves clinical accuracy	"Clinical accuracy."	AI supports better medical decisions.	Interview 12
Workflow efficiency gains	"Workflow efficiency."	Operational improvements are a key outcome.	Interview 12
International knowledge exchange	"International knowledge exchange."	AI enables cross-border learning.	Interview 12
New roles emerge from AI adoption	"New roles."	AI adoption changes organizational roles.	Interview 12
Integrated teams increase	"Integrated teams."	AI drives closer collaboration across functions.	Interview 12
Higher governance requirements	"Higher data and governance requirements."	Adoption increases organizational demands.	Interview 12
Responsibility shapes model architecture	"Responsibility shapes model architecture."	Ethical considerations influence technical design.	Interview 12
Data use constrained by responsibility	"Data use."	Responsible principles limit permissible data practices.	Interview 12
Deployment boundaries defined	"Deployment boundaries."	Clear limits are set on where and how AI is used.	Interview 12

Concept	Quote	Definition	Interview
Shift from product to enablement model	"Shift from AI products to an enablement model."	Business model reorients from selling tools to building capacity.	Interview 12
Infrastructure as core offering	"Infrastructure."	Value proposition centers on shared foundations.	Interview 12
Capacity-building focus	"Capacity-building."	Emphasis on developing local capabilities.	Interview 12
Multi-hub clinical validation	"Multi-hub clinical validation."	Business model relies on distributed validation sites.	Interview 12
Governance as main bottleneck	"Governance, not technology, is the core bottleneck."	Organizational governance is seen as key constraint.	Interview 12
Clinically led AI as necessity	"Clinically led models are essential."	Clinical leadership is framed as non-negotiable for safe AI.	Interview 12
Willingness for member checking	"Yes, you may contact me via email."	Openness to clarification supports dependability.	Interview 12
Top-down AI adoption	"It always comes from the top of the organisation."	AI initiatives are primarily initiated by senior leadership rather than operational staff.	Interview 13
Fear of missing out (FOMO)	"That is a fear of missing out."	Leaders adopt AI to avoid lagging behind perceived competitors.	Interview 13
Recurrent AI hype cycles	"Big data was like that… now LLMS AI is like that."	AI adoption follows repeated waves of technological hype (big data, ML, LLMs).	Interview 13
Echo chamber of success stories	"You hear only the people that has been successful."	Public discourse highlights successes while failures remain hidden, distorting expectations.	Interview 13
Consultant-driven AI narratives	"Many of them, driven by consultancy companies."	Consulting firms amplify AI success stories because it aligns with their business model.	Interview 13
Opportunity cost framing	"How much would cost if we don't do it now."	Leadership justifies AI by framing delay as more costly than immediate adoption.	Interview 13
Ring-fenced AI budgets	"I have this budget, the only condition is… spend it in AI."	Budgets are earmarked specifically for AI, pushing areas to "find"AI use cases.	Interview 13
National regulatory variation	"In Germany they are really strict."	Regulatory stance toward AI differs significantly between countries.	Interview 13
High-penalty enforcement	"If someone comes… like 10% of your revenue… that is painful."	Large potential fines incentivize organizations to comply strictly with regulation.	Interview 13
Healthcare as a special domain	"In healthcare… we are talking really sensitive data."	Healthcare is treated as distinct because of the sensitivity and persistence of medical data.	Interview 13
Long-term sensitivity of health data	"It doesn't matter when it's leaked… it's still valid for affecting my life."	Clinical data remains harmful even if disclosed many years later.	Interview 13
Multi-regulatory environment (GDPR, HIPAA)	"You have… GDPR… you have as well… HIPAA in United States."	Healthcare AI must comply with multiple overlapping regulatory regimes.	Interview 13
Governance via review boards	"They even put in place different review boards, different governance."	Organizations use formal boards and governance structures to oversee AI in healthcare.	Interview 13
Strict patient protection rules	"You can't use AI if it's going to affect in how to treat patients."	Direct clinical decision-making by AI is prohibited to safeguard patients.	Interview 13
Zero-risk tolerance in grey areas	"Even if it's a little bit on the grey area… we are not taking the chance."	Initiatives with ambiguous risk profiles are halted rather than explored.	Interview 13
Bias via proxy variables (ZIP code)	"You can't use… flip code… it's a proxy… may introduce bias."	Certain seemingly innocuous features are excluded because they indirectly encode sensitive attributes.	Interview 13
Regulation reduces usable data	"You're already blocking me any feature that I could use… to drive my predictions."	Bias and privacy constraints limit the feature space available for AI.	Interview 13
Shift from patient-facing to internal AI	"You have to target internal processes… instead of the processes… in front of the patients."	AI is redirected away from direct patient interaction toward back-office operations.	Interview 13
AI confined to process optimization	"It's limited to… process optimization, cost saving."	Under regulatory constraints, AI primarily supports internal efficiency gains.	Interview 13
AI not "in healthcare" but in its processes	"You're actually not doing AI in the healthcare, you're doing AI in the internal process."	Distinction between clinical AI and AI in surrounding organizational processes.	Interview 13
Money as core driver	"At the end of the day… it's all about the money."	Financial considerations dominate AI adoption rationales.	Interview 13
Labor substitution through automation	"You have a process… instead of 100 people you only need 20 people."	AI is used to replace human workers to save costs.	Interview 13
Hybrid automation + AI due to hallucinations	"People are trying to do a kind of hybrid between automation and using this kind of AI."	Current LLM limitations lead to blended architectures combining deterministic automation and generative AI.	Interview 13
Ethics currently not main driver	"Ethics are not the main driver right now."	Ethical and societal considerations are presently secondary to feasibility and cost.	Interview 13
Anticipated labor-protecting regulation	"Some kind of regulation… may block… replacing people."	The Interview expects future rules limiting workforce replacement by AI.	Interview 13
Replacement as "easy" saving strategy	"Right now the easier target… almost every organisation… is replacing people."	Substituting labor is seen as the simplest path to savings.	Interview 13
Concern about vendor concentration	"Benefits… go to three vendors."	AI value accumulates with a small number of large technology firms.	Interview 13
Vendors richer than countries	"Some of these vendors… worth more than actual countries."	AI vendors' scale raises macro-political and economic concerns.	Interview 13
Need for taxation and redistribution	"Some kind of taxation redistribution… I would expect it to happen."	Suggests policy mechanisms to redistribute AI-derived gains.	Interview 13
Politicians arrive late to regulate AI	"Our politicians… always come late to the party."	Sees regulation as reactive and temporally lagging behind technological practice.	Interview 13
Pre-regulation data scraping	"Open AI scraped all Internet… four years later you have to pay rights."	Example of firms exploiting legal grey zones before rules tighten.	Interview 13
Conditional market access as leverage	"If you want your AI to be used in European Union… you're gonna need to pay."	Foresees using access to EU markets as leverage for redistribution.	Interview 13
Mixed expertise on governance boards	"It's a mix… people that actually know… and people that just want to be there."	Governance bodies combine genuine experts with opportunistic participants.	Interview 13
Model provenance as first governance check	"First… which model are you using?"	Governance processes start by scrutinizing which AI model is chosen and its origin.	Interview 13
Risk of unapproved or foreign models	"You're picking up something from Internet… with very sensitive data."	Highlights dangers of running unvetted or geopolitically problematic models.	Interview 13
Data and feature scrutiny for bias	"Are you sure… it doesn't include any bias, any proxy metrics?"	Governance requires careful evaluation of dataset composition and feature selection.	Interview 13
Clarifying intended use of AI output	"What are you going to use the outcome of this model for?"	Intended application is examined to ensure AI is not used for impermissible decisions.	Interview 13
Human-in-the-loop requirement in HR	"A model can't say we have to fire this person, has to be a person."	Some domains mandate human decision-making despite AI input.	Interview 13
Thorough pre-deployment testing	"You can't sip to production something that has a 50% accuracy."	Models must reach robust performance before deployment.	Interview 13
Monitoring and retraining for drift	"How are you going to check… if your model is still behaving as expected?"	Ongoing monitoring and possible retraining are essential lifecycle governance steps.	Interview 13
Healthcare review depth and rigor	"People actually sit down… really investigate… it's a lengthy process."	Healthcare AI undergoes particularly detailed and time-consuming review.	Interview 13
Top-down panic leading to misfit	"Leaders come panicking… you're going to apply it to the wrong problem."	Leadership anxiety can push AI into ill-suited use cases.	Interview 13
Preference for explainable models	"We prefer… a little bit lower… if it was coming with some explainability."	Slightly less accurate but interpretable models are favored over opaque ones.	Interview 13
Black-box risks of neural networks	"With neural networks… you don't know what is happening inside."	Neural networks are seen as problematic because of their opacity.	Interview 13
Justification logs for AI decisions	"It gives you a justification… why this is the outcome of this process."	Systems generate textual rationales to support transparency and auditing.	Interview 13
Using logs to debug recommendations	"You can go to the log… and check it out in justification."	Justifications help diagnose whether errors stem from data changes or reasoning flaws.	Interview 13
Present "gold rush" funding phase	"People are dumping big budgets on this right now."	AI is currently in a generous, low-scrutiny investment phase.	Interview 13
Anticipated budget tightening	"Budgets are going to be shrinked."	The Interview expects a forthcoming reduction in AI spending.	Interview 13
Future ROI accountability	"What is this generating for the company?"	Organizations will increasingly demand demonstrable returns from AI initiatives.	Interview 13

Concept	Quote	Definition	Interview
Decorative or "toy" AI deployments	"They don't generate anything… it's just like a signing toy."	Some AI use is mainly symbolic, serving to signal innovativeness rather than create value.	Interview 13
Pendulum from hype to pragmatism	"It's a pendulum… they revert to very basic simple machine learning."	Over time, organizations move from over-complex AI back to simpler, cost-effective methods.	Interview 13
"Good enough" performance threshold	"Sometimes 99, 97 is good enough."	Near-optimal accuracy can be acceptable if it reduces cost or complexity.	Interview 13
AI as analytical tool, not decision-maker	"AI is a tool; it doesn't take decisions."	Frames AI as supportive infrastructure rather than autonomous actor.	Interview 14
Responsibility lies with humans, not AI	"AI cannot be responsible; people behind it are."	Rejects the idea of AI itself being morally responsible.	Interview 14
Black-box nature limits responsibility claims	"We don't know how neural networks work inside."	Argues that opacity undermines claims of responsible AI.	Interview 14
Critiques European focus on premature AI ethics	"Europe uses ethics too early without clarity."	Views EU ethical framing as premature and conceptually unclear.	Interview 14
Regulation before understanding slows innovation	"Europe regulates what it doesn't understand yet."	Sees early regulation as a barrier to experimentation and learning.	Interview 14
Prefers experimentation before regulation	"Test first, regulate later if it's harmful."	Advocates exploratory use prior to restrictive governance.	Interview 14
AI can be beneficial or harmful depending on use	"AI can create drugs or be used for surveillance."	Emphasizes dual-use nature of AI technologies.	Interview 14
Business models must start from real problems	"A business must fix a problem, not an idea."	Grounds business model innovation in concrete user needs.	Interview 14
Rejects "changing the world" narratives	"Everyone says they will change the world."	Criticizes vague, hype-driven startup rhetoric.	Interview 14
Companies exist primarily to make money	"Companies are created to make money."	Frames profit as legitimate and necessary business objective.	Interview 14
Value creation precedes ethical debate	"First create value, then discuss ethics."	Suggests ethics should follow demonstrated usefulness.	Interview 14
European startups lack market orientation	"Europe has good scientists, not good sellers."	Diagnoses weak commercialization capabilities.	Interview 14
Startups lack clear go-to-market focus	"They don't know who will pay for this."	Notes absence of defined customer and revenue logic.	Interview 14
MVP absence undermines trust	"They enter the market without an MVP."	Identifies lack of minimum viable products as systemic problem.	Interview 14
Papers are mistaken for products	"They think a publication is what they sell."	Critiques academic mindset dominating startups.	Interview 14
Trust erodes when products are overpromised	"People stop believing in AI after bad experiences."	Links failed implementations to loss of societal trust.	Interview 14
Misused AI damages institutional credibility	"You lose authority in front of the public."	Sees AI misuse as reputational risk for healthcare institutions.	Interview 14
Patient trust is central for AI adoption	"If patients don't trust it, it fails."	Frames legitimacy as prerequisite for adoption.	Interview 14
Competing with big tech requires niche focus	"It's David against five Goliaths."	Warns against competing head-on with large AI firms.	Interview 14
AI startups must target specific use cases	"Why not solve one concrete problem?"	Argues for focused, problem-specific AI solutions.	Interview 14
European mindset resists risk-taking	"People are afraid of risk here."	Attributes slow innovation to cultural risk aversion.	Interview 14
Leadership must provide direction under uncertainty	"A leader cannot say 'I don't know'."	Associates effective leadership with exploratory action.	Interview 14
Inaction creates organizational paralysis	"When the leader is blocked, everyone panics."	Describes consequences of indecisive leadership.	Interview 14
Risk management should be learned capability	"Managing risk must be trained."	Frames risk-handling as skill rather than avoidance.	Interview 14
Repeating same actions prevents change	"Doing the same thing gives the same results."	Advocates behavioral change to achieve innovation.	Interview 14
Mindset change is prerequisite for AI future	"Europe needs a change of mindset."	Concludes that cultural transformation is necessary for AI progress.	Interview 14
Automated clinical note generation	"Generate the clinics note fast without… human interference."	Uses AI to automatically produce clinical notes from interactions.	Interview 15
Regional differences in AI adoption speed	"Each country has that different regulations and different speed of the adoption."	Observes that countries vary in regulation and implementation pace.	Interview 15
India prioritises speed due to doctor shortage	"We are looking for the speed because we require the solution in fast way… lacks of doctors."	In India, workforce shortages drive rapid AI deployment.	Interview 15
Europe perceived as highly regulated and slow	"In Europe I see like there are lots of regulations… process is very slow."	Views EU MDR and regulatory processes as slowing AI rollout.	Interview 15
Same data protection principles across regions	"Same data protection laws… in India also… UAE… Europe also."	Argues that core data protection rules are similar globally.	Interview 15
Longer timelines for data collection in Europe	"Data collection in India it's taken 3 months which… here maybe 6 to 9 months."	Compares significantly slower European data collection processes.	Interview 15
Working closely with radiologists for AI diagnostics	"We have the doctors… radiologist who… bring the knowledge of the healthcare side."	Collaborates with radiologists to define diagnostic targets for AI.	Interview 15
Clinical experts define what AI should detect	"They… guide us… what thing you have to find in the image using AI."	Doctors specify clinically relevant features for AI detection.	Interview 15
Translating technical outputs into medical context	"I have to convert the technical means output in terms of the medical context."	Mediates between technical predictions and clinical meaning.	Interview 15
Long-term collaboration with doctors	"I'm working almost more than six years with the doctor."	Stresses extended experience collaborating with clinicians.	Interview 15
Understanding doctors' thinking and expectations	"I know their psychology, how they're thinking, how they wanted output."	Claims deep familiarity with clinicians' mental models and needs.	Interview 15
AI outputs as probabilistic predictions	"AI… most of the prediction based or the probability based out-put."	Frames AI results as probabilistic rather than deterministic truths.	Interview 15
Designing inputs according to required outputs	"How to define this input context according to the… output is required."	Emphasises careful input design to match desired clinical outcomes.	Interview 15
Viewing healthcare as business with money flow	"Healthcare is also business… insurance paying the money… money flow is going on."	Frames healthcare AI impact partly in terms of economic structures.	Interview 15
Assessing AI impact on existing business	"How my AI solution will be helpful for this existing business."	Evaluates solutions by their contribution to current healthcare business models.	Interview 15
Measuring added detection beyond doctors	"How many tumour my AI can detect where doctor are miss-ing."	Uses "missed tumours"as a concrete impact metric for diagnostic AI.	Interview 15
Regulatory bodies as key healthcare stakeholders	"In healthcare I can say the regulatory bodies required."	Identifies regulators as distinctive stakeholders compared to other sectors.	Interview 15
Need for medical device certification	"I required to get the certain certificate like… EU MDR in Eu-rope."	Highlights certification requirements for AI as medical device/software.	Interview 15
Country-specific health authority approvals	"In UAE there is… Dubai health authority… which certificate you require."	Notes local health authorities governing AI deployment.	Interview 15
General-purpose AI restricted in healthcare	"Now there are no any healthcare related diagnostics… because this is under regulars."	Observes that general LLMs have removed diagnostics due to regulation.	Interview 15
Healthcare as highly regulated AI domain	"In the Healthcare is like one of the biggest regulations in the world."	Perceives healthcare as having exceptionally strict AI regulation.	Interview 15
Need for explainability of AI decisions	"Explainability of the AI how you predict your means disease."	Emphasises explainability requirements for clinical acceptance.	Interview 15
Localising predictions to disease area	"Explain… where your AI actually predict the things."	Expects spatially explicit explanations (e.g., lesion regions).	Interview 15
AI as supportive tool with human in the loop	"This tool cannot replace them. This tool helping them to reduce their burden."	Frames AI as augmenting, not replacing, clinicians.	Interview 15
Dual translation between technical and clinical worlds	"Convert my technical words into the medical contacts and… medical to… technical world."	Describes bidirectional translation as central to AI–clinical collaboration.	Interview 15
AI design varies by disease and patient condition	"In each context like AI is differ… according to disease… pa-tient conditions."	Rejects one-size-fits-all AI, stressing clinical specificity.	Interview 15
Healthcare AI rollout slower than other sectors	"In the other business is very easy to roll out the AI but in healthcare is difficult."	Contrasts simplicity of AI adoption in non-health domains with healthcare complexity.	Interview 15

Concept	Quote	Definition	Interview
Need to build doctors' trust and confidence	"You have to take the confidence of the doctor… this tool cannot replace them."	Trust-building is central to successful adoption.	Interview 15
Understanding existing clinical workflows before deploying AI	"You have to understand… what is going on medical side and then rolled out your point."	Argues for deep understanding of current practice before proposing AI.	Interview 15
Identifying concrete problems in current system	"Then you point out which is the… problem in the existing system."	Advocates problem-driven, not technology-driven, AI design.	Interview 15
Constraints from GDPR and hospital access	"I cannot communicate directly with the hospitals… my AI will be put… in the hospitals premises."	Describes GDPR and hospital-controlled infrastructure as deployment constraints.	Interview 15
Requirement to use certified health cloud infrastructure	"If I'm putting in the cloud then I have to go some particular… telemetric… cloud services."	Must use approved national telehealth clouds for cloud-based AI.	Interview 15
Fewer private hospitals slow rollout in Europe	"There are less private hospitals over here… compared to other part of the world."	Links public-sector dominance to slower adoption.	Interview 15
Private hospitals in Dubai and India adopt faster	"Private hospital… directly willing to take your solution… they already have their own systems."	Contrasts faster, less bureaucratic adoption in private settings.	Interview 15
Frustration about slow European rollout	"If not getting that means… give me frustration."	Expresses personal frustration with long European timelines.	Interview 15
Desire for solutions within 1–2 years	"I need this solution in the one year or two year."	Articulates preferred innovation timeframe for healthcare AI deployment.	Interview 15
AI clinic note generation as major impact	"AI Power Clinic note generation… doctor and patient conversation can be recorded."	Identifies automated note-taking as highly impactful use case.	Interview 15
Global rollout of AI clinic note tools	"Almost rolled out in every part of the world."	Views clinical note generation as widely adopted internationally.	Interview 15
Use of LLMs and speech-to-text in documentation	"Based on LLM and… speech to text conversion."	Describes technical stack enabling clinic note generation.	Interview 15
Diagnostics require multimodal data integration	"Mammogram is… one context but… further test you require like blood tests or other tests."	Emphasises need to combine imaging, lab tests and clinical data.	Interview 15
Incorporating family history and clinical data	"You have… family history and… other clinical data… combine this all the data."	Recognises holistic diagnostic reasoning beyond single modality.	Interview 15
Generalised diagnostic models unlikely	"I not see that all diagnostic solution will be generalised."	Predicts locally constrained diagnostic AI rather than global models.	Interview 15
Regional or country-based diagnostic AI	"It is a regional base or the country based solutions."	Expects AI tailored to demographic and regulatory contexts.	Interview 15
Big tech must localise models to regions	"They have to put their models into particular country or particular reason to train them."	Anticipates in-country training/deployment for compliance.	Interview 15
Health data not allowed to leave Germany	"In Germany we cannot take the data outside from Germany in the health care."	Notes data localization rules as barrier to centralised training.	Interview 15
European Health Data Space (EHDS) as future enabler	"They are making the… European health data exchange… rolled out in 2029."	References EHDS as upcoming framework for intra-EU data sharing.	Interview 15
Energy- and resource-intensive frontier models	"You require lots of money, lots of energy, lots of computational power… people are fighting for the energy."	The Interview highlights that developing large AI models is no longer feasible for most actors due to extreme energy, compute, and financial demands.	Interview 15
Training frontier models now out of reach for startups	"Time is over for the developing of this kind of models… you require lots of money"	Believes only big tech can train large foundation models.	Interview 15
Startups should apply existing models to local problems	"What is existing models… how you use that and solve your problem."	Advocates leveraging foundation models rather than building new ones.	Interview 15
Big tech cannot solve all local problems	"They cannot… figure out all the problems of the society."	Sees space for local innovators despite big tech dominance.	Interview 15
Acquisition of local startups by big tech	"They maybe take over or maybe acquire the startup who… solving the problem of that region."	Envisions consolidation via acquisition of specialised local firms.	Interview 15
Agentic AI to harmonise clinical decisions	"Same data is same but the decision is differ… this kind of problem can be solved by AI."	Suggests agentic AI can reduce variability in clinical judgement.	Interview 15
Agentic AI for faster patient data retrieval	"Helping doctors to get the information fast from the system."	Sees agents as tools to query patient history efficiently.	Interview 15
Querying previous medications via agents	"Which medicine I take previously… directly you see in the screen."	Envisions conversational retrieval of medication history.	Interview 15
Using previous cases and research for decision support	"Using… previous best cases or previous published research… get… information how to treat this patient."	Agentic/LLM systems aggregate precedent and literature for guidance.	Interview 15
Need for regular AI education in public sector	"Regular requirement of the… sessions to the… public hospitals… regarding this AI."	Advocates recurring training on AI's role and design principles.	Interview 15
Public misperceptions of AI as threat	"Many… see AI will be trade or AI is taking their job."	Notes fear of job loss due to AI among healthcare workers.	Interview 15
Explaining how AI can be useful	"How this technology can be useful? We have to spread that thing."	Stresses communication of AI's positive contributions.	Interview 15
Patient-facing AI solutions seen as harmful	"Many solutions… directly try to do the patient which is… harmful for the patient."	Criticises AI tools that bypass professional medical oversight.	Interview 15
Risk of patients self-medicating based on AI	"I take the medicines… from the AI prescribe me which may be harmful for me."	Highlights dangers of patients acting on AI suggestions without clinicians.	Interview 15
AI should reach patients via proper channels	"Your AI solution can be go through the proper channel… hospital or… doctor."	Argues for mediated, clinician- or hospital-led AI delivery.	Interview 15
Life-critical nature of AI-supported decisions	"Decision… take your life also if there are strong decision."	Emphasises that AI-influenced choices can be life-or-death.	Interview 15

Appendix F - Full Gioia Coding Structure

Concepts	Sub-Themes	Themes	Dimension
AI as radiology second reader / second opinion Machine vision converts images to diagnoses AI superior when trained on millions of images AI will come strongly in ultrasound Radiology will be massively automated Normal X-rays will no longer be reviewed by humans Existing hospital-wide AI for chest X-ray analysis Thorax AI performance currently judged as poor Future AI potential in coronary angiography image analysis AI will automate routine radiology findings AI helpful for specific quantitative tasks AI valuable for staging & volumetry Automated volumetry mandated in screening Lung cancer screening requires AI by regulation Scanner-integrated AI improves quality & speed Purchased AI "acceleration modules" are valuable	AI-supported diagnostic imaging and radiology	Applying AI in Diagnostic Imaging and Complex Cases	Augmentation
AI app for EKG-based heart-attack detection AI detects subtle EKG changes better than doctors Smartphone photo workflow for AI ECG interpretation AI could support ECG and BP analysis AI could help filter artefacts in long-term ECG Routine ECG holds little AI benefit Remote device monitoring via AI already emerging EKG analysis system likely already AI-supported Tumor board decision support with partial automation AI could recommend stent type, size and inflation pressure Diagnostics require multimodal data integration Incorporating family history and clinical data Generalised diagnostic models unlikely Regional or country-based diagnostic AI	AI-enabled cardiology and specialized diagnostic support		
Research–bedside gap in robotics and AI Respect, uncertainty and time concerns around robotics Surgical robotics show high precision High potential of AI and robotics at bedside Assistive technologies for communication with intubated patients AI robotics still require human oversight	Robotic and embodied AI in clinical and surgical settings		
AI used only in rare diagnostic edge cases Open to complex-case AI assistance AI as idea generator and first insight for difficult decisions Using previous cases and research for decision support Agentic AI to harmonise clinical decisions AI as evidence tool for complex differential diagnoses	AI-assisted support for complex and rare clinical cases		
AI for speech-based documentation and coding support AI eases complex medication dosing Automated clinical note generation AI clinic note generation as major impact Use of LLMs and speech-to-text in documentation Global rollout of AI clinic note tools AI-generated drafts used as templates for presentations Sources checked and content revised after AI drafts AI not yet used personally for documentation Patients will receive AI-driven automated reports Uses speech-recognition tool for dictation AI system improves shared access vs paper records	AI-driven clinical documentation automation	Automating Clinical Documentation and Administrative Tasks	
AI helpful for phone & appointment management Possible AI use for inventory & procurement Scheduling already semi-automated but needs oversight New practice will integrate AI-enabled systems Will adopt AI modules if offered with new systems AI confined to process optimization AI not "in healthcare" but in its processes Agentic AI for faster patient data retrieval Querying previous medications via agents Productivity tools like Copilot imagined as helpful Automating repetitive tasks to relieve system pressure	AI-enabled administrative and operational workflow support		
Improving quality through cleaner medical documentation Hospital-introduced AI medication system AI documentation enhances traceability of medication errors Documentation burden as major barrier to patient care time Desire for AI to reduce double documentation in ED AI as support to free time for core medical work Retrospective wish for AI in doctoral research AI could dramatically shorten research cycles Learning programming for research consumed years	Documentation quality improvement and administrative burden reduction		
Regulatory affairs dossier writing as prime AI use case Regulatory dossiers are cumbersome, repetitive and text-heavy AI can shorten dossier timelines and unlock major value RA specialists are scarce; AI should free them for higher-value thinking Extraction and transformation as core AI value AI expected to replace processing labour Labor substitution through automation Replacement as "easy" saving strategy Manual review of documentation is labour-intensive NLP demo as triggering event for AI conviction AI replaces repetitive data-extraction labour	Automation of repetitive clinical and administrative tasks		
Use of Open Evidence for validated study summaries AI helps navigate overwhelming journal landscape AI supports dosing and therapeutic decisions Open Evidence used for orientation then verified AI used to refresh knowledge and update evidence AI used for idea generation and scoping literature AI supports literature retrieval for rare findings AI-enabled differentials can outperform manual search AI-supported resources may be embedded in paid tools AI reduces administrative burden and focuses search ChatGPT as everyday clinical research assistant AI enables fast, easy-to-publish research ChatGPT provides quick answers to complex questions Retrospective source checking as 'open evidence' loop Emerging backbone infrastructures for knowledge capture Rating and surfacing best insights (Airbnb analogy) Generative AI accelerates coding and statistics work AI used as research and guideline shortcut Natural language to code as emerging capability Future semantic understanding of nuanced language	AI-based information retrieval and evidence synthesis	Retrieving Medical Information and Managing Workloads	
Translation use case as AI entry point AI supports translation and understanding documentation AI reduces language barriers for foreign physicians Supporting migrant doctors with language and documentation burden Improved translation across human and technical "languages"	Language and communication support for migrant healthcare professionals		
AI streamlines information retrieval Faster access to relevant studies and papers AI structures complex issues for faster comprehension Perceived faster and higher-quality decisions via AI AI frees physicians' time for targeted specialist research Efficiency gain as handling more tasks, not time saving AI supports higher-quality rather than faster work Explosion of imaging data requires AI AI can act as pre-reader for large image volumes	AI-supported workload management and capacity optimization		

Concepts	Sub-Themes	Themes	Dimension
Time scarcity as central barrier Limited time and regulatory capacity at employers Lack of time for explicit ethical reflection No perceived ethical concerns due to time pressure Strong workload prevents deeper AI engagement Lack of time for structured team reflection on AI Time pressure and perceived inability to involve stakeholders Workload makes acceptance-building doubly difficult Demographic staff shortages limit training capacity High workload reduces motivation to adopt AI Lack of time for peer knowledge exchange	Temporal constraints in clinical AI adoption and learning	Facing Time Scarcity and Workforce Shortages	Embedding
Demographic change and staff shortages as AI drivers AI as future necessity due to workforce shortage Demographic peak of workforce shortage as AI pressure AI as potential necessity due to workforce shortages Acute staffing crisis due to late technology adoption AI adoption driven by workforce shortages International competition for skilled healthcare workers Political resistance to migration constrains staffing Staff relief rather than staff saving as AI goal Telephone shortages drive AI scheduling Sees DoctorLib-style assistants as inevitable Hospital consolidation and economic pressure Rising patient age and acuity increase pressure Structural clinical challenges drive AI adoption Rising complexity motivates AI use Resource constraints as adoption driver India prioritises speed due to doctor shortage	Workforce shortages as drivers of AI-enabled care continuity		
Senior chief physician sceptical toward digital tech Distrust of AI vendor due to Eastern European base Surgeons' attitudes range from eager to resistant Learners' fear and lack of confidence using AI tools Low digital and AI literacy among experienced nurses Older non-digital-native colleagues struggle with AI AI optimization process is slow and generationally limited Generational transition in physician mindset Healthcare boards are older and conservative about AI Historical or accidental appointment of AI decision-makers Lack of basic AI literacy among decision-makers	Clinician skepticism and resistance toward AI technologies		
AI solutions perceived as too expensive No universal radiology AI; only narrow tools AI as third reader in mammography not reimbursed Patients resist paying extra for AI Lack of reimbursement for AI limits implementation Employer refuses to pay for clinical AI license Cost concerns as barrier to AI adoption No revenue benefit expected from AI Cost savings and digitalization as main AI introduction drivers High acceptance among radiologists if affordable Organization invests few resources in AI for daily work Commercialization paradox: users won't pay for their own knowledge Budget myopia blocks proactive AI investment	Economic and reimbursement barriers to AI adoption	Encountering Economic Pressures and Infrastructure Constraints	
Purely monetary expectations as red flag for AI projects Cheapest-solution bias undermining responsible AI No AI tools yet implemented in the practice AI may become relevant with new practice expansion No current need for faster report generation No current AI usage in the practice Money as core driver Anticipated budget tightening Future ROI accountability "Good enough" performance threshold Companies exist primarily to make money Viewing healthcare as business with money flow Assessing AI impact on existing business	Cost-efficiency–driven AI business model logics		
No closed internal AI system for documentation support Requirement to use certified health cloud infrastructure Constraints from GDPR and hospital access Health data not allowed to leave Germany European Health Data Space (EHDS) as future enabler Need for safe, bounded AI environments ("own garden") Gemini example of internal AI boundary Rapid evolution of enterprise AI offerings	Infrastructure and deployment constraints in healthcare AI		
Physicians self-initiating AI use Bottom-up AI adoption without strategy Autodidactic, bottom-up AI adoption by residents Informal collegial exchange normalizes AI use Peer recommendation as diffusion mechanism Conference encounter with AI developer triggers adoption Radiologists privately experiment with AI LLMs Informal testing of free LLMs with guideline scenarios Anonymized diagnosis lists tested in ChatGPT Free LLMs tested against guidelines and regulations AI used with some caution but minimal reflection Informal culture of collegial consultation for tough cases Open-minded consultants as AI allies Dual role as clinician and AI startup contributor Visibility and career opportunity drive AI engagement Regular use of two main AI applications	Bottom-up clinician-led AI experimentation and peer diffusion	Engaging in Grassroots Experimentation and Shadow AI Use	
Top-down AI tools imposed without consultation Staff not involved in tool choice or AI strategy Top-down technology procurement without co-design Top-down AI adoption Bottom-up use cases with top-down sponsorship Risk of uncontrolled bottom-up AI without leadership framework Limited involvement of frontline staff in vendor selection IT should not be sole driver of AI projects Middle managers feeling compelled to follow orders Snowball effect of successful AI pilots inside the firm Lack of interoperability between AI and letter system Copy-paste workaround between systems Persistence of poorly applicable tools in practice Top-down panic leading to misfit	Top-down and bottom-up implementation tensions in AI integration		
Use of private smartphones for clinical AI ("shadow AI") Risk of staff using unofficial AI tools (shadow AI) Path of least resistance leads to shadow IT (e.g., WhatsApp) Under-the-table use of public LLMs with anonymised data Private, governance-free experimentation with "shadow AI" Risk of employees using unapproved AI tools with confidential data Need for clear corporate AI provider agreements Research context more open to admitting AI use	Shadow AI use outside formal organizational governance		
AI as "today's fancy word" and hype driver Fear of missing out (FOMO) Recurrent AI hype cycles Echo chamber of success stories Consultant-driven AI narratives Opportunity cost framing Ring-fenced AI budgets Present "gold rush" funding phase AI seen as major trend in medicine Expectation of hype–correction cycle for AI Technology gold rush → tragedy → governance pattern SMEs are uncertain, fearful, and myth-driven about AI Warning that overly conservative firms risk obsolescence Analogy between AI today and the early internet era Decorative or "toy" AI deployments Pendulum from hype to pragmatism	AI hype cycles and fear-of-missing-out adoption dynamics	Navigating Hype-Driven Adoption and Pilot Experimentation	
Tech-first, ROI-driven AI adoption logic Tool selection before clarifying business case Critique of tool-first, top-down AI implementation Use-case driven AI strategy instead of tool-first Identifying concrete problems in current system Understanding existing clinical workflows before deploying AI Business models must start from real problems Rejects "changing the world" narratives High failure rate of AI projects due to shortcut mentality Tool-first approaches undermine change management and acceptance AI design varies by disease and patient condition Implementation pathway as crucial as technology Need for maturity assessments before AI projects Lack of clinically grounded AI as problem Shift from patient-facing to internal AI Startups lack clear go-to-market focus MVP absence undermines trust Papers are mistaken for products AI startups must target specific use cases Industry regularly offers AI solutions Receives AI vendor outreach via email or mail Vendor dialogue leads to incremental improvements	Problem-driven versus tool-driven AI adoption approaches		
Plan to sponsor multiple small AI pilot projects Using pilot results to encourage wider adoption Early validation in pilot hubs Pilot hubs enable structured experimentation Learning by doing, failing and "failing fast" AI benefits still uncertain but require experimentation Temporary project halting when risk unclear Prefers experimentation before regulation	Iterative piloting and experimental learning in AI implementation		

Concepts	Sub-Themes	Themes	Dimension
AI can misclassify rare patterns (button as tumor) AI cannot distinguish clinically irrelevant warnings AI requires narrow, domain-specific training Perceived ~80% diagnostic accuracy Quality and accuracy of AI expected to improve	AI performance limitations and hallucination risks	Addressing AI Errors and Demanding Clinical Validation	Legitimation
Error reduction as primary near-term AI value AI improves clinical accuracy Workflow efficiency gains AI will revolutionize diagnostic practice AI improves diagnostic accuracy through large datasets Ethical duty to use AI if evidence supports it	Error reduction and safety enhancement through AI support		
Clinical validation required Measuring added detection beyond doctors Evidence gap on AI's real impact Thorough pre-deployment testing Monitoring and retraining for drift Uncertainty whether current AI hype is justified Desire for evidence-based decisions over gut feeling	Clinical validation and continuous performance monitoring of AI systems		
No formal AI oversight structures or roles No lifecycle governance for AI systems AI use lacks organisational governance and documentation No formal stakeholder involvement in AI decisions Absence of guidelines for innovation–ethics tensions No formalized approach to AI-related conflicts Absence of dedicated AI roles or structures Frontline clinicians not involved in vendor-level resolution No structured pre-implementation impact assessment No formal AI-related decision process Governance resources lag behind AI investments Email-based collection of staff issues including AI Governance as main bottleneck Lack of consultation across ecosystem	Absence of formal AI governance and accountability structures	Establishing AI Governance Structures and Risk Oversight	
Governance as living, evolving document Early, practice-based governance rather than abstract rules Using internal LLM "governance bots" for policy access External monitoring layers to detect compliance and shadow AI Three-layer decision model Clinical leadership layer Technical governance layer Executive steering layer Clinical & Scientific Board oversight Model owners assigned Risk frameworks guide oversight Working groups support governance Lifecycle documentation maintained Drift monitoring Audits as routine practice Physician-led AI governance role Strategic oversight of AI projects Two designated AI contact persons for problem management	Strategic AI governance bodies and oversight committees		
Governance as key to data and patient safety Governance and ethics must be communicated to entire workforce Quality management leads external communication on AI Quality management monitors tools over time Internal governance focuses on data handling basics Intelligent systems increasingly govern themselves Self-updating algorithms challenge legal accountability Audit scope must match data and model dynamics Clinical quality assurance responsibility Governance design as core task Coordination of international pilot sites Governance bodies involved Transparency as daily design principle Guardrails embedded in models Monitoring influences daily decisions Automated risk triggers Principle-based escalation Innovation value balanced with safety	Operational AI governance processes and risk monitoring		
Healthcare AI spans trivial to high-risk Passive vs agentic AI distinction Need to bucket AI systems by sensitivity and agency Different buckets of sensitive information Distinct legal, regulatory and ethical layers "AI" label often misused for clever algorithms Legal liability largely covered by existing product/consumer law Zero-risk tolerance in grey areas Bias via proxy variables (ZIP code) Early consideration of ethical risks Structured impact assessment Scenario testing before deployment Risk identification as formal practice Stakeholder mapping Reflection built into AI lifecycle Joint physician–technical evaluation Broad stakeholder involvement	Risk-based classification of AI systems for governance purposes		
Higher governance requirements Responsibility shapes model architecture Data use constrained by responsibility Deployment boundaries defined Clinically led AI as necessity Willingness for member checking Governance via review boards Model provenance as first governance check Data and feature scrutiny for bias Clarifying intended use of AI output Healthcare review depth and rigor Pre-development reflection Mid-iteration reflection Pre- and post-deployment review Documentation of responsibility decisions	Embedding ethical and responsibility principles into AI governance	Embedding Ethical Reflection and Building Trust	
Everyday-technology analogies to build trust Humans can fail too, not only machines Need for holistic acceptance "head, heart, body" Relationship-based pedagogy to build AI trust Need to build doctors' trust and confidence Partial transparency about AI training data builds trust Informal knowledge exchange spreads understanding of AI origins Low adoption due to poor explanation and fears Trust erodes when products are overpromised Misused AI damages institutional credibility Patient trust is central for AI adoption Good firms delay AI to co-design with users Need for fast but structured consultation framework	Trust-building mechanisms for AI acceptance in clinical practice		
Responsibility and ethics implicitly reduced to data protection AI contacts focus on problem-solving, not ethics Hardly any time for responsibility or societal reflection Ethics seen as crucial but under-addressed for AI Ethics and legislation lag behind AI implementation Limited structured reflection spaces for AI Ethical obligation to future patients Societal risks considered in AI Long-term impact considered Ethics currently not main driver AI can be beneficial or harmful depending on use Value creation precedes ethical debate	Limited institutional capacity for ethical and societal AI reflection		
Data protection seen as essential baseline Emphasis on EU-compliant data protection in startup Data protection conformity assumed by default Data protection and compliance as practical gatekeepers Data protection officer and chief disapprove of careless AI use IT blocks new AI due to data sensitivity concerns Same data protection principles across regions Cloud processing raises primary privacy concerns Highly sensitive clinical content intensifies risk Cloud storage increases vulnerability Long-term sensitivity of health data Multi-regulatory environment (GDPR, HIPAA) Unawareness of GDPR and legal responsibilities Third-party data processing complicates responsibility Unclear ownership of model-enriched data	Data protection and privacy compliance as core AI governance focus	Complying with Data Privacy Regulations and Security Requirements	
Belief that data cannot really be misused because AI does not flag non-compliance Data always accessible to someone Data-propriety and leakage as dominant AI concern Company culture of digital and data paranoia Rejects passive audio recording tools Does not want AI recording and transcribing consults Low-security firewalls in GP practices Sensitive mental-health data risk severe consequences Transparency of structured diagnosis data is high Data easier to access than paper records Data-mining yields sensitive insights Strong ethical concerns about data hacking Medical data misuse could harm access to credit/insurance Data retrieval via ICD codes makes misuse easier AI will make data access even easier Risk of unapproved or foreign models Continuous attempts to breach data	Data security and misuse risks in healthcare AI		
Global regulatory divergence in AI for devices Different jurisdictions impose different consent regimes National regulatory variation Regulatory regimes (MDR vs. 510(k)) add complexity AI can help manage Need for medical device certification Country-specific health authority approvals General-purpose AI restricted in healthcare Healthcare as highly regulated AI domain EU AI Act as key external influence GDPR shapes AI development Accreditation requirements influence AI International partners shape expectations Legal frameworks like EU AI Act seen as important	Navigating international regulatory frameworks for medical AI		
Big Pharma has a very different AI starting point Regulatory pressure accelerates adoption Global Responsible AI trend Regulatory compliance prioritized over innovation High-penalty enforcement Healthcare as a special domain Strict patient protection rules Regulation reduces usable data Regional differences in AI adoption speed Big tech must localise models to regions Regulatory bodies as key healthcare stakeholders	Regulatory enforcement as a constraint on AI deployment		
Europe perceived as highly regulated and slow Longer timelines for data collection in Europe Frustration about slow European rollout Desire for solutions within 1–2 years Fewer private hospitals slow rollout in Europe European mindset resists risk-taking Critiques European focus on premature AI ethics Regulation before understanding slows innovation Regulatory strictness in healthcare as justified barrier Perceived international lag and half-measures in Germany Systemic missteps leading to structural lag Healthcare AI rollout slower than other sectors Private hospitals in Dubai and India adopt faster	Perceived regulatory rigidity within the European AI context		
Human in the loop for medication recommendations Human-in-the-loop to resolve AI–clinician disagreements Human retains full responsibility for decisions Humans handle difficult decisions without AI No automated or AI-based final decisions AI viewed as supportive knowledge tool, not decision-maker AI treated as idea generator, not decision-maker Escalation of questionable AI outputs to liaison staff AI suggestions sometimes overridden by clinical context Human judgement as irreplaceable safeguard Human will remain for serious-case conversations Human in the loop as ethical requirement Need for human oversight ("human in the loop") Necessity of human plausibility checks Official AI outputs explicitly require human review Human revision needed due to hallucinations AI interaction checks require explicit acknowledgement System blocks orders if warnings not accepted	Human-in-the-loop oversight and retained clinical responsibility	Maintaining Human Oversight Amid Black-Box Opacity	
Physician-dominated AI decision-making Physician expertise and authority remain primary Case-specific clinical decision-making AI avoided in high-stakes qualification decisions Responsibility embedded in individual physician judgement AI used as confirmation of pre-existing diagnostic concept Gold standard shifting from human to software Humans only partially "in the loop" AI work ultimately impacts patient healthcare Personal lens focused on frontline care Selective involvement based on patient benefit Patient safety takes precedence Human-in-the-loop requirement in HR AI as analytical tool, not decision-maker Responsibility lies with humans, not AI AI will further simplify data access	Primacy of physician expertise over algorithmic recommendations		
AI perceived as 'black box' Black-box nature limits responsibility claims Black-box risks of neural networks Lack of transparency about other AI tools Underlying studies too complex for AI to fully capture Human–technology–data transparency as critical success factor Risk of trust erosion when AI outputs surprise users Hybrid automation + AI due to hallucinations	Opacity and black-box challenges in AI decision-making		
Need for explainability of AI decisions Localising predictions to disease area Explainability as requirement Justification logs for AI decisions Using logs to debug recommendations Preference for explainable models AI outputs as probabilistic predictions	Preference for explainable and interpretable AI systems		

Concepts	Sub-Themes	Themes	Dimension
Co-creation and continuous competence development Need to train users on language and bias in AI interactions AI literacy as societal goal by 2030 Need for regular AI education in public sector Explaining how AI can be useful German Radiological Society offers AI training Internal discussions drive AI learning Desire for external coaching and working groups Reliance on external experts for AI competence Self-education and user-level AI familiarity Limited inter-practice knowledge sharing	AI literacy and capability development through training and education	Developing AI Literacy and Addressing Training Gaps	Reconfiguration
Initial AI training sessions with partial attendance Peer-to-peer learning for late joiners Ongoing ad-hoc support for colleagues' prompts One-off trainings with learning-by-doing afterwards Vendor-provided initial trainings with sign-off Formal AI training perceived as medico-legal, not practical Generative AI training prohibits public tools Need for protected time windows for AI learning	Skill and confidence gaps due to insufficient AI training		
Self-developed AI assessment criteria for student work Regulatory and curricular vacuum on AI in education Pending state curriculum mandating digital & AI content Education must incorporate lessons learned from practice Misalignment between education and practice timelines Physicians teach robotics, educators take AI topics AI enhances training Educators act as translators of legislation into curricula	Institutional gaps in formal AI education within medical curricula		
Need for heterogeneous, cross-functional AI project teams Best practice: dedicated change managers and UX with domain experts Diverse development teams reduce bias in AI systems Interdisciplinary teams support AI Holistic 360° approach and admitting limits Building internal AI "community of practice" Selecting open departments and extroverted heads for pilots Mixed expertise on governance boards Neglected employee participation in AI design Cross-functional evaluation of conflicts Integrated teams increase	Cross-functional collaboration in healthcare AI development	Fostering Cross-Functional Collaboration and Cultural Support	
Leadership and culture as key internal enablers Leadership belief in AI combined with bottom-up enthusiasm Clinical leadership enables AI adoption Digital maturity as internal enabler Strong safety culture Importance of executive sponsorship for AI change Suggestion for CEO-level AI budget and ownership Embedding AI initiatives into managers' objectives Leadership must provide direction under uncertainty Need to educate and reassure the board about AI Necessity of bringing the board along to secure investment Inaction creates organizational paralysis Risk management should be learned capability Repeating same actions prevents change Mindset change is prerequisite for AI future	Leadership support and experimentation-oriented organizational cultures		
Working closely with radiologists for AI diagnostics Clinical experts define what AI should detect Translating technical outputs into medical context Long-term collaboration with doctors Understanding doctors' thinking and expectations Designing inputs according to required outputs Dual translation between technical and clinical worlds Bridge-builder between technology and practice	Clinician–AI expert collaboration in model development and interpretation		
AI should augment, not replace, clinicians (10-year horizon) AI as supportive tool with human in the loop Unsure whether AI can replace physicians Belief that AI will replace radiologists Fear that physicians could "abolish themselves" Physician self-reflection needed to stay relevant Low-effort physicians more replaceable Manual, invasive specialties less replaceable Non-invasive specialties more vulnerable to automation Neurology perceived as less automatable Analysis shifting from humans to machine systems Humans retain comparative advantage in creativity Dermatology and radiology highly replaceable Manual, invasive procedures less replaceable Dermatology and radiology particularly vulnerable	Augmentation versus replacement tensions in clinical AI adoption	Confronting Job Displacement and Shifting Care Models	
Concern about radiologists' job future under AI Radiology demand will collapse Anticipated labor-protecting regulation Public misperceptions of AI as threat Employee concerns about data, transparency, and job security European startups lack market orientation Concern about vendor concentration Vendors richer than countries Need for taxation and redistribution Politicians arrive late to regulate AI Pre-regulation data scraping Conditional market access as leverage Competing with big tech requires niche focus Energy- and resource-intensive frontier models Training frontier models now out of reach for startups Startups should apply existing models to local problems Big tech cannot solve all local problems Acquisition of local startups by big tech	Employment disruption and power concentration concerns		
Shift from product to enablement model Infrastructure as core offering Capacity-building focus Multi-hub clinical validation Vision of massively expanded physician panel size Analogy between AI era and early internet AI-driven business model changes remain hypothetical Insight as distinct and valuable asset Anticipated market for stakeholder-management specialists Founders face tension between ideals and survival GP becomes central coordinator of AI-enabled care AI transforms diagnostic pathways AI will generate specialist-level findings for GPs House physicians become central coordinators International knowledge exchange New roles emerge from AI adoption	AI-enabled role transformation and capacity-building futures		
AI as inevitable and needing "AI for good" framing AI as one important lever among others AI will revolutionise healthcare AI adoption as necessary to prevent system collapse Traditional analogue care model at breaking point AI enables parallel processing and digital assistants Global access to "smartest mind" via ubiquitous AI AI as a major future driver in medicine	Perceived inevitability of AI-driven healthcare transformation		
Patients increasingly use ChatGPT for self-information Patient AI research sometimes correct and helpful Patient-facing AI solutions seen as harmful Risk of patients self-medicating based on AI AI should reach patients via proper channels Life-critical nature of AI-supported decisions Non-disclosure of AI use to patients Difficulty explaining limited AI use (grammar only) AI use for letters triggers patient data protection concerns Transparency towards patients about AI and robotics Ethical aspects considered in patient-facing communication	Patient engagement and transparency in AI-supported care		