# MASTERS IN MANAGEMENT (MIM)

## MASTERS FINAL WORK

DISSERTATION

# STRATEGIC IMPLICATIONS OF AI ADOPTION IN HEALTHCARE: THE CASE OF EMERGENCY ROOM TRIAGE SYSTEMS

NICOLAS ZISS

APRIL - 2026

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**SUPERVISOR:** PROF. RICARDO MARINO FRANCISCO RODRIGUES

**JURY:**

**PRESIDENT:** PROF. MARIA EDUARDA MARIANO AGOSTINHO SOARES

**RAPPORTEUR:** PROF. FLÁVIO ALEXANDRE COSTA ROMÃO

**SUPERVISOR:** PROF. RICARDO MARINO FRANCISCO RODRIGUES

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# Resumo

Os sistemas de saúde em todo o mundo enfrentam desafios significativos, como a sobrelotação. Porém, a implementação da Inteligência Artificial (IA) na triagem de emergências apresenta dificuldades organizacionais substanciais. Pouco se sabe sobre a complexa interação entre integração clínica, adaptação organizacional e aceitação do utilizador, além da viabilidade técnica.

Esta dissertação examina as implicações estratégicas da adoção de Sistemas de Apoio à Decisão (DSS) baseados em IA na triagem de emergências e como os hospitais podem alinhar a inovação tecnológica com objetivos organizacionais mais amplos. Utilizando uma abordagem qualitativa com uma amostra de oito stakeholders (executivos hospitalares, médicos, pessoal de enfermagem e estudantes de medicina), os resultados revelaram uma desconexão fundamental entre a ambição estratégica e a prontidão operacional.

As conclusões destacam uma «lacuna na capacidade da infraestrutura», em que a falta de hardware básico impede a criação de valor, juntamente com um «paradoxo de utilidade-usabilidade», em que os elevados encargos de introdução de dados anulam a utilidade percebida dos sistemas. O panorama de adoção torna-se ainda mais complexo devido a uma «lacuna de perceção estratégico-operacional» em relação à governação, levando a uma «aprendizagem informal» e a riscos de erosão da competência entre os funcionários juniores. Estas percepções contribuem para a literatura sobre a Perspetiva Baseada em Recursos e Aceitação de Tecnologia na área da saúde, incluindo recomendações valiosas e práticas para a gestão priorizar a higiene digital e a governação participativa.

**Palavras-Chave:** Triagem de emergência, Inteligência Artificial, Sistemas de Apoio à Decisão, Gestão estratégica, Adoção de tecnologia, Preparação organizacional

**JEL Codes:** O32; I11; M15; O33; M10

# Abstract

Healthcare systems globally face significant challenges like overcrowding, yet the implementation of Artificial Intelligence (AI) in emergency triage poses substantial organisational difficulties. Little is known about the complex interplay between clinical integration, organisational adaptation, and user acceptance beyond technical feasibility. This thesis examines the strategic implications of adopting AI-based Decision Support Systems (DSS) in emergency triage and how hospitals can align technological innovation with broader organisational objectives. Using a qualitative approach with a sample of eight stakeholders (e.g., hospital executives, physicians, nursing staff, and medical students), the results revealed a fundamental disconnect between strategic ambition and operational readiness. Findings highlight an "infrastructure-capability gap" where missing basic hardware hinders value creation, alongside a "utility-usability paradox" where high data-entry burdens negate the perceived utility of the systems. The adoption landscape becomes even more complex due to a "strategic-operational perception gap" regarding governance, leading to informal "shadow learning" and risks of competence erosion among junior staff. These insights contribute to the literature on the Resource-Based View and Technology Acceptance in healthcare, including valuable, practical recommendations for management to prioritise digital hygiene and participatory governance.



**Keywords:** Emergency triage, Artificial Intelligence, Decision Support Systems, Strategic management, Technology adoption, Organizational readiness

**JEL Codes:** O32; I11; M15; O33; M10

## Declaration of Independence and Use of AI

I hereby certify that I have completed this work independently in its entirety and have not used any sources or aids other than those indicated in the work, and that the work has not been submitted in the same or a similar form in any other examination. I have used generative AI applications to gather information and/or revise my text. I have independently verified the results found using AI applications and have made them my own. The AI-based tools used were ChatGPT and DeepL.

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# Abbreviations

| Abbreviation | Meaning |
|---|---|
| AI | Artificial Intelligence |
| DC | Dynamic Capabilities |
| DRG | Diagnosis Related Group |
| DSS | Decision Support Systems |
| ED | Emergency Department |
| IoT | Internet of Things |
| KHZG | Hospital Future Act |
| LLMs | Large Language Models |
| Mdn | Median |
| PEOU | Perceived Ease of Use |
| PU | Perceived Usefulness |
| RBV | Resource-Based View |
| SOPs | Standard Operating Procedures |
| TAM | Technology Acceptance Model |
| VRIO | Valuable, Rare, Inimitable, and Organized |
| XAI | Explainability AI |

# 1. Introduction

Healthcare systems around the world are facing significant challenges, including increased patient volume, crowded emergency rooms, and more complex medical cases (El Arab & Al Moosa, 2025). Emergency triage, the quick sorting of patients by the urgency of their medical needs, is essential to ensuring that patients receive the care they need on time and that resources are used effectively. This process has typically relied on clinical expertise, but Artificial Intelligence (AI) is changing it substantially, mainly through Decision Support Systems (DSS) (Tyler et al., 2024).

Patil and Shankar (2023) state that these kinds of systems not only make activities faster and more accurate, but they also give hospitals strategic chances to become more competitive, digitally mature, and improve the quality of their services. There is considerable debate about how well AI-driven triage systems work. Still, their use raises broader questions about an organisation's readiness, how it is run, and how well its goals are aligned. Research indicates that AI tools can attain significant accuracy and efficiency in clinical decision-making (Preiksaitis et al., 2024; Siira et al., 2025). However, their use in emergency care settings must be carefully considered in terms of ethical risks, accountability, and the trust of all parties involved (Nord-Bronzyk et al., 2025). Hospitals must therefore confront the dual challenge of leveraging AI's performance capabilities while strategically integrating these systems into established frameworks and long-term goals (Magrabi et al., 2023).

Despite increased awareness and a growing body of literature on AI in healthcare, there are still crucial shortcomings in current research. Recent studies have primarily focused on technical performance and proof-of-concept feasibility, often neglecting the complex interplay among clinical integration, organisational adaptation, and user acceptance (Siira et al., 2025; Tyler et al., 2024). More specifically, existing research rarely examines infrastructure readiness, user acceptance and governance perceptions as interdependent conditions for AI adoption in emergency triage, despite their combined relevance for strategic value creation. Drawing on Hassan et al. (2024), it becomes evident that purely technical perspectives are insufficient for understanding the challenges of AI adoption in high-stakes environments such as emergency triage. Specifically, there is a lack of integrative research that connects organisational resource readiness with the individual acceptance realities of medical staff and the dynamic adaptation processes required in daily practice. As noted in recent reviews, while the technical potential is well documented, the organisational soil required for these systems to flourish remains insufficiently examined (Hassan et al., 2024; Siira et al., 2025).

To address this complexity, this MFW draws on three complementary theoretical perspectives to analyse the challenge. The Resource-Based View (RBV) holds that organisational resources can serve as enduring sources of competitive advantage if they possess value, rarity, inimitability, and organisational integration (Barney, 1997). When applied to AI-based triage systems, this perspective underscores their importance to hospitals' long-term strategy. Second, the Dynamic Capabilities (DC) framework underscores a firm's capacity to assimilate, develop, and reconfigure internal and external resources to respond to swiftly evolving environments and technological advancements (Teece et al., 1997). This MFW further expands this perspective to include institutional pressures (Oliver, 1997) that may affect the implementation of AI in emergency care. Third, the Technology Acceptance Model (TAM) highlights the importance of perceived usefulness and perceived ease of use in influencing users' willingness to adopt new technologies (Davis, 1989). In healthcare, this illustrates how healthcare professionals' perceptions can affect the implementation of AI systems in emergency triage. User acceptance is a key factor in the success of AI integration in hospitals, with trust in technology among the most important factors (Lambert et al., 2023). In emergency triage, where timely decisions are crucial, healthcare professionals' acceptance of AI may be pivotal to effective implementation.

Despite increased awareness and a growing body of literature on AI in healthcare, significant gaps remain. Recent studies have primarily focused on technical performance and proof-of-concept feasibility, whereas aspects such as clinical integration, organisational adaptation, and user acceptance have received insufficient attention (Siira et al., 2025; Tyler et al., 2024). Drawing on Hassan et al. (2024), it becomes clear that purely technical perspectives are not sufficient to understand AI adoption in healthcare. Strategic alignment, organisational capabilities, and the acceptance and engagement of healthcare professionals are also important for successful implementation. Their review emphasises that there is comparatively less work on consolidating barriers and facilitators in a joint perspective, underscoring the need for stronger connections between governance and implementation frameworks that account for patient perspectives and sociotechnical contexts.

Trust is a crucial element, influenced by transparency, fairness, and ethical protections, and it requires governance frameworks that encompass the entire AI lifecycle and are supported by explicit regulatory and legal direction (Hassan et al., 2024).

To fill the research gap, the research question that guides this MFW is: "What are the strategic implications of adopting AI-based DSS in emergency triage, and how can hospitals align their implementation with broader organisational objectives and capabilities?"

There are three main goals of this MFW. First, to investigate the reasons and expected benefits of using AI in triage systems and the barriers preventing their realisation. Second, to look at how these technologies fit with the goals and abilities of the organisation, such as digital maturity and governance structures. Third, to assess the impact of technology acceptance factors among clinicians and other stakeholders on the strategic success of adoption.

To accomplish these objectives, the MFW follows a qualitative, exploratory research approach. Semi-structured interviews with hospital executives, physicians, nursing staff, and medical students will capture a range of perspectives on the implementation of AI. A complementary analysis of hospital strategies and industry reports will provide context for the findings. The data will undergo thematic content analysis, concentrating on the identification of frequent patterns related to strategic alignment, capability development, and acceptance determinants.

This MFW makes two important contributions. Theoretically, it synthesises RBV, DC, and TAM into a cohesive framework to better understand AI adoption in critical healthcare settings. This approach enables the collection of information on both organisational and individual-level factors that affect strategic outcomes. In practice, the MFW provides recommendations for healthcare leaders. First, this MFW provides an in-depth empirical account of how strategic ambition and operational reality diverge in the context of AI-based triage systems, based on multi-perspective qualitative data from a hospital setting. Second, it contributes theoretically by integrating the Resource-Based View, Dynamic Capabilities and the Technology Acceptance Model into a coherent analytical framework tailored to high-stakes healthcare environments. Third, it offers practical implications for healthcare leaders by outlining how technological innovation can be aligned with governance structures, organisational capabilities and user acceptance.

The MFW is structured as follows: the initial section is a literature review that brings together research on AI in healthcare and explains the theoretical basis. Second, the methodology section provides detailed information on the qualitative research design. Third, the results of the interviews and document analysis are shown. Fourth, the discussion integrates empirical results with the theoretical framework. In the end, the MFW concludes with implications for theory and practice, limitations, and future research directions.

# 2. Literature Review

This chapter examines existing research on strategic technology management in healthcare, focusing on the application of AI in emergency medicine, alignment with organisational goals, and the necessary governance and ethical RBV, DC, and TAM for answering the research question.

## *2.1 Strategic Technology Management in Healthcare*

Strategic technology management in healthcare involves actively integrating digital innovations into organisational strategy and aligning technological progress with institutional goals (Huebner & Flessa, 2022).

Digitalisation is discussed in terms of efficiency gains, but also as a driver for the development of new business models and the influencing of organisational culture (Angerer et al., 2022). Therefore, hospitals are encouraged to view digital technologies from a strategic management perspective rather than treating them exclusively as operational tools (Huebner & Flessa, 2022).

Digital transformation requires an infrastructure that can integrate different information systems and support advanced technologies such as the Internet of Things (IoT), cloud computing and interoperability (Gopal et al., 2019). The IoT connects physical devices and sensors, enabling continuous data collection and supporting new forms of preventive and personalised care (Kelly et al., 2020). Cloud computing provides scalable, on-demand computing resources, allowing hospitals to manage workloads and data flows flexibly (Gopal et al., 2019). Interoperability ensures seamless data exchange between different systems; however, fragmented IT landscapes remain a significant challenge in healthcare (Gopal et al., 2019).

The concept of digital maturity is crucial for making the most of technological innovations. Hospitals with higher levels of maturity can integrate digital resources into their strategies more effectively (Gopal et al., 2019). Without such maturity, hospitals risk keeping digital initiatives isolated, failing to generate long-term benefits for organisational performance (Angerer et al., 2022). Specific technologies highlight the strategic potential and challenges of digitalisation. Big data analytics provides descriptive, predictive and prescriptive insights that support clinical decision-making and optimise resource use, although governance and privacy concerns remain pressing (Khanra et al., 2020). The IoT also improves continuous and preventive care through wearable and implantable devices (Kelly et al., 2020). It requires robust security measures and standardisation to gain acceptance among healthcare professionals and patients (Kelly et al., 2020). Blockchain technologies can enhance data integrity and transparency, but their implementation is complicated by regulatory uncertainty, limited awareness, and high costs (Saeed et al., 2022).

The strategic importance of digital technologies became clear during the pandemic, when artificial intelligence, big data and the IoT proved crucial for the prevention, diagnosis and treatment of the virus (Ye, 2020). Meanwhile, open innovation models fostered swift collaboration across organisational boundaries and accelerated the development of healthcare solutions (Z. Liu et al., 2022). 5G networks are critical because they support telemedicine, telesurgery and connected emergency services by providing high-speed, low-latency connections (Cabanillas-Carbonell et al., 2023).

Based on these findings, it is clear that digital transformation in healthcare is a strategic necessity requiring organisational readiness and a long-term focus on institutional goals (Huebner & Flessa, 2022). This is particularly true in emergency departments (ED), where the complexity, time pressure and limited resources make adopting new technologies more challenging (Raita et al., 2019). Against this backdrop, AI-based DSS for triage have attracted attention due to their potential to improve outcome prediction and facilitate clinical decision-making in time-critical situations (Y. Liu et al., 2021). However, this MFW focuses specifically on the adoption of AI–based DSS and their implications in emergency triage.

### *2.2 Artificial Intelligence in Emergency Medicine*

AI in emergency medicine is defined as the use of data-driven computational technologies, most notably machine learning and deep learning, to aid time-sensitive decision-making at the point of care by learning from large, partially unstructured clinical data sets (Grant et al., 2020). Specifically, AI-based DSS differ from static rule-based tools in that they learn from data and generate predictions that clinicians can use to aid triage, diagnostic reasoning, and operational decisions in the ED (Grant et al., 2020). Similarly, AI-enabled DSS complements clinician judgment by translating multimodal inputs into prioritised, actionable recommendations, while fully accounting for the fast-paced, high-acuity demands of emergency medicine (Grant et al., 2020). An example of modality breadth is the use of image recognition alongside clinical information to facilitate visual tasks that aid in triage and diagnosis in radiology (Okada et al., 2023).

DSS applications in the ED have focused on acuity assessment and triage. Models synthesise vital signs, presenting symptoms, and clinical history to improve patient prioritisation in high-volume, time-pressured settings (Piliuk & Tomforde, 2023). Beyond the triage of patients, AI has the potential to monitor patient flow by predicting waiting time, patient outcomes, and admissions. This has implications for staffing decisions and capacity management, helping to address bottlenecks (Grant et al., 2020).

In practice, large language models (LLMs) offer similar capabilities, providing real-time triage support, helping draft differential diagnoses, and summarising patient records, thereby reducing the burden of documentation in high-acuity settings (Preiksaitis et al., 2024). Studies that map the ED AI literature demonstrate two classification systems: one focused on diagnostics and the other on triage. These systems are applied to tasks such as risk stratification, severity estimation, outcome prediction, and urgency prioritisation (Piliuk & Tomforde, 2023).

In all circumstances, there are opportunities to improve efficiency through the automation of workflows, the optimisation of diagnostic support and the potential improvement of resource allocation through predictive operations when overcrowding is a consideration (Preiksaitis et al., 2024). In addition, studies report that AI-based tools may reduce cognitive burden and help standardise decision-making, especially in the triage process. This is because early decisions can have significant implications for the patient’s entire clinical care process (Grant et al., 2020). At the same time, the explainability of AI models is essential for gaining professional trust and acceptance for use, as clinicians often view a model that cannot be understood as a “black box” within high-stakes contexts (Okada et al., 2023).

Practical challenges may have included difficulties integrating AI into existing ED workflows, as well as the retrospective nature and single-site design of most studies, which may have affected their validity, generalizability, and applicability to external settings (Piliuk & Tomforde, 2023). Commentaries, therefore, posit that careful consideration and assessment of modular, narrowly scoped tools are essential for addressing specific pain points that EDs experience, such as rapid triage and documentation, and for scaling with existing IT infrastructures and policymakers (Grant et al., 2020).

Finally, the LLMs literature highlights the promise and limitations of the technology. It emphasises the importance of multidisciplinary stakeholders for setting objectives so that models support clinical judgement while improving care efficiency, without undermining safety or reducing equitable care (Preiksaitis et al., 2024). While these applications demonstrate the technical potential of AI in the ED, their implementation must be driven by overarching organisational objectives to generate genuine value.

### *2.3 Organisational Goals and the Strategic Value of AI Adoption*

To fully realise the potential of the AI technologies described in the previous section, the introduction of an AI-based DSS in the ED is grounded in strategic management principles aimed at achieving key organisational goals (Huebner & Flessa, 2022). From this perspective, the introduction of technology is not an end in itself, but a means of creating sustainable value by improving service quality, ensuring patient safety through error reduction, and securing competitiveness under significant economic pressure (Grant et al., 2020). The potential of AI to optimise resource allocation and improve operational efficiency is particularly noteworthy, as it offers a way to ensure excellent care with existing or even reduced resources (Almyranti et al., 2024). However, this requires that technological capabilities be closely aligned with an organisation's long-term institutional goals and digital maturity, a process that requires the development of DC, a theoretical concept further analysed in Chapter 2.4, to identify and exploit new opportunities (Gopal et al., 2019; Teece et al., 1997). The successful implementation of AI depends on this strategic alignment, which ensures that investments lead to measurable improvements in clinical and operational outcomes, such as reduced patient wait times, optimised throughput, and reduced cognitive and administrative burden on frontline staff (Boonstra & Laven, 2022; Preiksaitis et al., 2024). Beyond technical alignment, successful implementation depends on how the technology is framed within the organisation. Edmondson et al. (2001) distinguish between implementation as a mere technology installation versus a collective team learning process, arguing that treating innovation simply as a plug-in solution often leads to failure.

In the specific context of the German healthcare system, these general strategic considerations are reinforced by several unique institutional factors. The prevailing diagnosis-related group (DRG) based reimbursement model creates a strong incentive for the efficiency gains promised by AI, making it an important tool for cost containment (Huebner & Flessa, 2022). At the same time, the national strategy for the digitalisation of the healthcare system and the recent implementation of the EU AI Act create both momentum and a strict regulatory framework for the introduction of AI (Baumgart & Kvedar, 2025; Busch et al., 2024). This environment requires German hospitals to develop robust internal governance structures for algorithmic control that comply with both national priorities and European regulations on data protection and AI risk management (Van Kolfschooten & Van Oirschot, 2024; Zhang & Zhang, 2023). Furthermore, strategic objectives may differ between public hospitals, which focus on fulfilling a public mandate, and private hospital groups, which may prioritise profitability and market positioning (Huebner & Flessa, 2022). Taken together, these findings suggest that the strategic value of AI for German hospitals is realised at the confluence of general organisational goals and the specific pressures of the national and European regulatory and economic landscape. To understand the theoretical mechanisms that enable organisations to capture this value and sustain competitive advantages, the following section analyses AI adoption through the lens of established management theories.

### *2.4 Theoretical Perspective on AI Adoption*

To theoretically ground the strategic potential of AI outlined in the previous section, the RBV provides a fundamental framework for understanding how organisations attain and sustain a competitive advantage (Barney, 1991). Specifically, the evolved valuable, rare, inimitable, and organised (VRIO) framework suggests that, to achieve this, resources must meet these four criteria, meaning the organisation itself must be structured to effectively capture their value (Barney, 1995, 1997). In the healthcare system, digital technologies such as AI may be regarded as strategic resources when linked to unique datasets or proprietary algorithms, as these characteristics can create valuable, rare, inimitable, and organised advantages (Cubric, 2020; Roppelt et al., 2024). However, recent extensions of the RBV suggest that possession of resources alone is insufficient. Sirmon et al. (2007) introduce the concept of resource management, emphasising that organisations must effectively bundle and structure their portfolio of resources to realise any competitive advantage. Whether resources produce competitive outcomes also depends on institutional factors and mechanisms that determine how resources are deployed (Oliver, 1997).

Nevertheless, the RBV has been criticised for its limitations in highly dynamic environments, as static resource characteristics may not guarantee long-term advantage (Priem & Butler, 2001). In the context of this MFW, this issue is particularly relevant for rapidly evolving fields such as digital health.

These discussions illustrate that the strategic utility of technological resources depends considerably on institutional congruence and legitimisation (Oliver, 1997). Building on this limitation and the requirements for adaptability mentioned in Chapter 2.3, the DC perspective builds on and extends the RBV, focusing on how organisations develop the capacity to integrate, build, and reconfigure competencies in fast-changing environments (Teece et al., 1997). Rather than being abstract, DC consists of specific and identifiable organisational and strategic processes, such as product development, strategic decision-making, and forming alliances, that firms use to reconfigure their resource base in dynamic and high-velocity markets (Eisenhardt & Martin, 2000). In healthcare, this suggests that gaining a competitive advantage depends less on AI as a standalone resource and more on hospitals' ability to adapt workflows, data infrastructure and governance to AI-enabled processes (Eisenhardt & Martin, 2000; Roppelt et al., 2024). Empirical research on the adoption of AI suggests that the ability to recognise opportunities, social adaptability to work with stakeholders, and the adaptability of production responsiveness to integrate systems into workflows are key factors in the utilisation of innovations (Gao et al., 2025). Furthermore, capability development is not always a formalised top-down process. Research by Beane (2019) demonstrates that when formal training is decoupled from operational reality, staff may develop informal capabilities through shadow learning or deviant practices to bridge the gap.

Whilst the concepts of RBV and DC are relevant in specific organisational contexts (Barney, 1995; Teece et al., 1997), the TAM focuses more on the role of individual users' perceptions in technology adoption (Davis, 1989). According to Davis (1989) the acceptance of such technologies is primarily predicted by two factors: perceived usefulness (PU) and perceived ease of use (PEOU). While these factors predict the intention to use a system, they do not necessarily guarantee value realisation. (Burton-Jones and Grange (2013) address this by proposing the concept of effective use, which posits that a system is only truly accepted when its usage aligns with the user's task goals to create transparent value. Research in healthcare settings has shown that PU and PEOU are significant predictors of technology acceptance. In the context of AI-based decision support systems, acceptance is also strongly influenced by perceived clinical utility and the degree of integration into existing workflows (Khanijahani et al., 2022). To illustrate this point, research conducted with nurses indicates that perceived adoption barriers for integration were influenced by training and perceived decision support (Ramadan et al., 2024). However, these barriers were found to be influenced by perceived ethical reasons or perceived threats to autonomous decision-making (Ramadan et al., 2024).

Synthesised evidence indicates that governance structures and institutional readiness are critical factors shaping AI adoption, beyond users' recognition of its importance and utility (Hassan et al., 2024). Further evidence shows that facilitators and barriers occur across multiple levels, from individual attitudes to institutional structures and broader societal factors, underlining the multi-layered nature of AI acceptance (Henzler et al., 2025).

As regards integration, research indicates that employee- and organisational-level factors are closely interrelated and should be considered holistically (Khanfar et al., 2025; Roppelt et al., 2024). Systematic reviews on AI adoption highlight that technological, individual, organisational, and environmental factors are interdependent and should therefore be examined in an integrated manner rather than in isolation (Khanfar et al., 2025). Similarly, the literature emphasises that employee attitudes and organisational readiness are mutually interdependent, underscoring the need for multilevel approaches (Roppelt et al., 2024). Finally, consolidated findings confirm that professional, organisational, and patient factors all shape adoption outcomes and need to be studied together (Khanijahani et al., 2022).

While these theories explain the potential for competitive advantage and user acceptance, their actual implementation in clinical practice is constrained by ethical obligations and risk management, as discussed in the following section.

### *2.5 Governance, Ethics, and Risk Considerations in AI Adoption*

While the theoretical frameworks discussed previously emphasise the value and acceptance of resources, the responsible use of medical AI requires governance mechanisms to promote transparency, accountability, and data protection (Zhang & Zhang, 2023). Hence, detailed documentation of datasets, including unambiguous descriptions of the data source, the dataset's content, and acknowledged limitations, is advised to increase transparency and identify and address bias, which can worsen health disparities (Alderman et al., 2025). Consensus recommendations call for transparent documentation of datasets and evaluations of model performance across population groups (Alderman et al., 2025). Fiske et al. (2025) highlight that fairness in medical AI relies on the explicit definition and documentation of sensitive variables (e.g., race and ethnicity), with sustained ethical justification of care, processes, and meaningful stakeholder involvement from the perspectives of patients, clinicians, or affected community members to uphold accountability and trust.

However, AI-mediated decision-making entails substantial risks and uncertainty. Bias poses a greater risk because training datasets are unrepresentative and poorly documented, leading to systemic errors in clinical outcomes (Alderman et al., 2025). In addition to data-related issues, Tikhomirov et al. (2024) point out that diagnostic dissonance between algorithmic predictions and clinical judgment can complicate effective oversight and impair decision quality if responsibilities and boundaries of use are not appropriately defined. Freyer et al. (2024) caution that LLMs introduce additional uncertainty, as their outputs are inherently variable and can hallucinate, and that these outputs cannot be reliably benchmarked for patient safety if utilised without proper confidence measures. Recent models can achieve diagnostic accuracy comparable to that of physicians (Levine et al., 2024). However, triage performance remains inconsistent, as they sometimes under-prioritise emergent cases or over-prioritise non-urgent ones, which further supports the rationale for continued human oversight (Levine et al., 2024). Furthermore, the limited availability of prospective randomised controlled trials leaves the robustness of the evidence and the potential unintended harms uncertain, underscoring the need for greater rigor in clinical validation (Han et al., 2024).

Concurrently, regulatory and ethical frameworks are evolving. With the EU AI Act entering into force in 2024, requirements such as transparency obligations, systemic risk analyses, robust cybersecurity measures, and incident reporting have been introduced (Freyer et al., 2024). Nevertheless, the regulation of LLMs in healthcare remains contested, as their risks differ substantially from those of conventional AI software (Freyer et al., 2024). Researchers note the need to enforce current medical device regulations but highlight that generative models still pose risks distinct from those of typical AI software (Freyer et al., 2024). Standards and reporting frameworks such as Good Machine Learning Practice, as well as CONSORT-AI, SPIRIT-AI, DECIDE-AI, and TRIPOD-AI, have emerged to establish transparency and reproducibility standards for clinical AI reporting (Alderman et al., 2025). At the institutional level, Zhang and Zhang (2023) emphasise the importance of algorithmic stewardship, real-world evaluation, and governance structures that incorporate equity monitoring and stakeholder engagement to ensure trustworthy implementation.

For emergency triage, where time-critical and ethically sensitive decisions are made, governance requirements become particularly important. Transparent dataset documentation, fairness metrics co-developed with stakeholders, continuous real-world evaluations, and clearly defined accountability structures are essential to fulfilling ethical obligations, mitigating risks, and ensuring accountability in life-and-death scenarios.

# 3 Methodology

This chapter describes the methodological approach and qualitative research design used to answer the research question "What are the strategic implications of adopting AI-based DSS in emergency triage, and how can hospitals align their implementation with broader organisational objectives and capabilities?" It includes semi-structured in-depth interviews, a qualitative content analysis based on Mayring (2015), and a deductive–inductive coding strategy that identified key themes and structural dimensions. The sample selection, data collection procedures, and analytical strategies are presented to ensure a robust and transparent research framework.

### *3.1 Sample and Procedures*

The qualitative research approach was chosen because it allows for an in-depth exploration of context-dependent phenomena. This approach facilitates the unravelling of processes, the exploration of meanings and an increased comprehension of complex systems. Compared to quantitative research, it involves capturing rich data, such as individuals' experiences and beliefs (Bryman, 2016). Qualitative research enables exploration of data that cannot be retrieved through direct measurement; such data can only be grasped through interaction and personal dialogue (Maxwell, 2009). Qualitative research enables knowledge co-creation, meaning that personal conversations between researchers and participants enable deeper investigations and extensive data collection. The flexibility of communication and the ability to adjust to real-time interactions can uncover additional insights (Guba & Lincoln, 1994). Furthermore, participants' narratives and subjective interpretations facilitate the sharing of thought processes and decision-making insights (Creswell, 2013). Observing participants' latent meaning is vital to the qualitative research approach (Charmaz, 2012).

To capture the complexity of AI adoption in emergency care through multiple stakeholder perspectives, this MFW applies purposive sampling (Creswell, 2013). Semi-structured, in-depth interviews were conducted with eight participants. The participants were selected through targeted sampling to ensure that data were collected from individuals with specific expertise or knowledge (Patton, 2000). Decision-making and acceptance in clinical practice are shaped by various professional groups (Henzler et al., 2025). Therefore, all participants were recruited from within the same hospital organisation but represented diverse roles: emergency physicians, intensive care nurses, prospective doctors, and hospital management. This internal diversity provided multiple perspectives on the strategic, clinical, and organisational implications of AI adoption, thereby enhancing the credibility and depth of the qualitative findings (Creswell, 2013).
To ensure anonymity while preserving the context of hierarchical positions, each participant was assigned a unique alphanumeric code. These codes, outlined in Table 1, indicate both the professional role and the level of seniority and are used throughout the subsequent analysis to attribute quotes and perspectives accurately.

Table 1

*List of Interview Participants*

| Code | Role | Experience Level |
|---|---|---|
| **MGMT-1** | Management | Senior Executive (General Management) |
| **MGMT-2** | Management | Senior Executive (IT Leadership) |
| **PHYS-1** | Physician | Senior Physician (Oberarzt) |
| **PHYS-2** | Physician | Senior Physician (Oberarzt) |
| **NURS-1** | Nurse | Senior Nurse (>20 years experience) |
| **NURS-2** | Nurse | Junior (Academic background) |
| **JUN-1** | Medical Student | Junior / Student |
| **JUN-2** | Medical Student | Junior / Student |

*Note:* The codes are used throughout the analysis to ensure anonymity and facilitate role-specific comparisons. Source: Own creation.

The sample size was determined following the concept of information power proposed by Malterud et al. (2016), which posits that the number of participants required in qualitative research depends on the specificity of the research aim, the quality of dialogue, the participants' expertise, and the analytical strategy applied. Given the focused research question, the targeted selection of participants with specific expertise, and the theory-guided analytical approach, eight interviews, two per expert group, were considered sufficient to provide information-rich data with high information power (Malterud et al., 2016). This is consistent with Guest et al. (2006), who note that a moderate number of interviews can yield substantive thematic insights when the sample is purposively selected and the research question is narrowly defined.

In this context, analytical depth was achieved not through the number of interviews but through the deliberate inclusion of distinct organisational roles, allowing the study to capture structurally different perspectives on the same adoption process. To guarantee that the data collection process provided relevant insights into individual experiences and perspectives, several complementary interview guides were created: one for doctors working in the ED and other settings; one for intensive care nurses; one for prospective doctors; and one for hospital management (Fontana & Frey, 2000). The questions were tailored to align with the professional positions of the participants (see Appendix A). To ensure theoretical alignment and construct validity, the interview guide was operationalised based on established frameworks. Table 2 outlines the thematic categories and their correspondence with the TAM (Davis, 1989), the RBV (Barney, 1997), and the DC (Teece et al., 1997). It further illustrates how these constructs were adapted to address the specific perspectives of emergency staff, prospective doctors, and hospital management.

Table 2

*Operationalisation of the Interview Guide and Theoretical Mapping*

| Category / Theme | Theoretical Basis | Objective & Key Constructs | Exemplary Areas of Inquiry |
|---|---|---|---|
| *1. Introduction & Background* | Contextual Foundation | Role clarity and baseline responsibilities. | Role definition; Current responsibilities in the emergency room |
| *2. Perception & Acceptance* | TAM (Technology Acceptance Model) | Capturing Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). | Expectations regarding AI; Areas of support (e.g., triage); Influence on willingness to use; Explainability. |
| *3. Org. Integration & Resources* | RBV (Resource-Based View) | Assessment of tangible and intangible organizational assets/resources. | Necessary technical resources (IT); Involvement in decision-making; Management support. |
| *4. Adaptability* | DC (Dynamic Capabilities) | Ability of the team/organization to integrate, build, and reconfigure competencies. | Team adaptability; Knowledge sharing processes; Competencies and training needs. |
| *5. Strategic & Ethical* | RBV / TAM | Strategic assets (long-term contribution) and Trust/Risk factors. | Long-term strategic value; Ethical concerns (bias, trust); Prerequisites for lasting acceptance. |

*Note.* The specific wording of questions was tailored to each stakeholder group (e.g., Emergency Nurses vs. Hospital Management) to ensure relevance (see Appendix A for complete interview protocols).

Alongside predominantly open-ended questions, selected items employed five-point likert-type scales to capture participants' perceptions, such as PU and ease of use, in a more structured and comparable way. The numerical ratings in all figures are used exclusively as a descriptive heuristic to visualise perceived patterns and discrepancies across stakeholder groups and do not imply statistical significance or generalisability.

Before the main data collection, a pilot interview was conducted to test the protocol, revealing the potential for adjustments and content refinement. This step ensured that such probing methods support the gathering of more comprehensive insights and the uncovering of underlying connotations (Rubin & Rubin, 2005). The interview protocol ultimately facilitated a more extensive sharing of opinions, viewpoints, and perspectives (Patton, 2000).

Regarding the final procedures, the interviews, which lasted 30-60 minutes, were conducted via videoconferencing on MS Teams. The questions explored perceptions, experiences, and the strategic implications of adopting AI-based DSS in emergency triage. Data collection was conducted using digital recording tools in MS Teams with participants' prior permission. As the interviews were conducted in German, all direct quotations presented in this MFW were translated into English by the author. Great care was taken to ensure that the translations accurately reflect the original meaning and context of the participants' statements.

### *3.2 Analytical Strategy*

The empirical data were analysed using a theory-guided qualitative content analysis based on the methodological approach proposed by Mayring (2015) and further developed for computer-assisted analysis by Kuckartz (2018). This approach was chosen because it allows for a systematic and transparent analysis of qualitative interview material while maintaining a clear link to established theoretical concepts. As the aim of this MFW is to examine and explain the strategic implications of adopting AI-based DSS in emergency triage, qualitative content analysis provides an appropriate analytical framework. Rather than generating new theory, the analysis seeks to integrate and empirically apply existing theoretical perspectives.

The analysis was primarily focused on the substantive object of investigation: the organisational, strategic, and individual conditions that influence the adoption and use of AI-based DSS in emergency departments. The interview texts were therefore not treated as linguistic or narrative objects in their own right, nor as biographical accounts of the interviewees. Instead, they were understood as expert-based sources that provide insight into organisational practices, decision-making processes, acceptance-related considerations, and governance challenges within a specific institutional context. In line with Mayring's (2015) understanding of qualitative content analysis, the interviewees were regarded as knowledgeable informants whose statements reflect role-specific experiences relevant to the research question.

The smallest unit of analysis consisted of meaning-bearing text segments, typically sentences or short passages, while the context unit was defined as the complete interview transcript. The analysis unit was formed from thematically structured categories that captured recurring, analytically relevant patterns across the interviews. The analytical process followed a combined deductive–inductive logic. In the initial step, a set of deductive main categories was developed based on the study’s theoretical framework. These categories were derived from the TAM, particularly the concepts of PU and PEOU (Davis, 1989), the RBV with its focus on strategic resources and value creation (Barney, 1995), and the DC framework, which emphasises organisational adaptation and reconfiguration in dynamic environments (Teece et al., 1997). In addition, institutional and governance-related aspects were incorporated, drawing on literature highlighting the importance of legitimacy, regulation, and organisational context in technology adoption (Hassan et al., 2024; Oliver, 1997).

For each deductively defined category, clear definitions and coding guidelines were established before analysis to ensure consistency and transparency. During the coding process, the interview material was reviewed repeatedly. When relevant aspects emerged that were not adequately captured by the original category system, inductive subcategories were developed within the existing framework. This procedure allowed the analysis to remain open to empirically grounded insights while retaining a clear theoretical orientation, as recommended by Kuckartz (2018).

All coding and analytical steps were conducted in MAXQDA, a widely used software tool in qualitative social science research. MAXQDA supported the systematic organisation of codes, the documentation of analytical decisions through memos, and the structured comparison of coded segments across interviews and stakeholder groups (Kuckartz & Rädiker, 2019). While the software facilitated transparency and traceability, interpreting the data remained the researcher's responsibility (O’Kane et al., 2021).

Following the coding phase, the analysis focused on identifying similarities, differences, and recurring patterns across the interviews, with particular attention to contrasts between professional groups, including emergency physicians, nursing staff, prospective doctors, and hospital management. This comparative perspective enabled examination of how individual acceptance factors, organisational resources and capabilities, and governance structures interact in practice. To support this comparative analysis, the numerical ratings collected via likert-type scales during the interviews are utilised as a descriptive heuristic. These values serve solely to visualise perceived discrepancies and patterns among stakeholder groups (triangulation of perspectives). Given the qualitative research design and the small sample size (N=8), these scores indicate tendencies and are not intended to claim statistical significance or generalizability. In a final step, the empirical findings were related to the theoretical framework to explain under which conditions AI-based DSS can contribute to strategic value creation in hospitals and where limitations or tensions arise.

# 4. Findings

This chapter presents the empirical findings derived from the qualitative content analysis of the expert interviews. It outlines the recurring themes and structural dimensions identified in the study and explains their significance for the adoption of AI in emergency care.

## *4.1 Technological Foundations: The Infrastructure Capability-Gap*

Analysing the organisation's readiness through the lens of the RBV reveals a fundamental disconnect between its strategic ambition and operational reality. While the organisation aims to deploy AI to gain a competitive advantage, the analysis indicates a critical deficiency in the complementary resources required. This phenomenon, identified here as the *infrastructure-capability gap*, suggests that the potential value of AI remains inaccessible due to a lack of tangible assets. Importantly, this gap does not reflect an absence of strategic intent, but rather a lack of complementary tangible resources required to operationalise existing strategic ambitions.

At the strategic level, the perceived potential of AI aligns with the value criterion of the VRIO framework, as stakeholders articulate a clear vision of AI as a driver of efficiency and quality. MGMT-1 emphasises the objective of using AI to support "decisions in the sense of economic efficiency" and to optimise clinical processes.

Similarly, JUN-2 highlights the transformative scope of the technology, noting that “the possibilities are incredibly vast” regarding operational efficiency. This view is shared by senior clinical staff, with PHYS-1 expressing the expectation that AI will help “to reduce error rates and speed up processes”. Theoretically, the intangible asset AI strategy is thus present and valued.

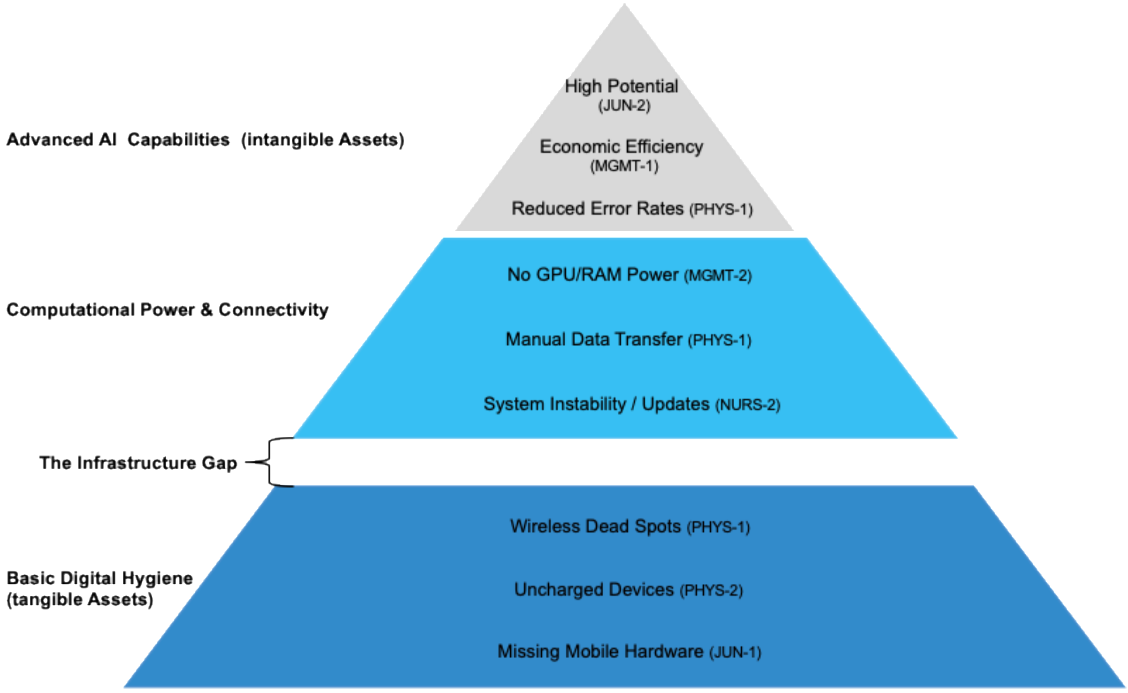
However, the realisation of this strategic value is hindered by a substantial deficit in tangible assets, specifically, the physical IT infrastructure required to deploy digital tools at the point of care. Consequently, in the terminology of Barney's (1995) VRIO framework, the analysis reveals that the organisation is not yet organised to capture value. While IT management (MGMT-2) asserts that a “good basis” has been established through recent digitisation initiatives, operational staff describe a work environment lacking “basic digital hygiene.” This deficiency manifests primarily in physical unavailability and connectivity issues. For instance, PHYS-2 describes how mobile workstations, critical for real-time AI support, are often rendered useless by simple maintenance failures, stating that “often, ward round carts are standing there with batteries that need constant charging... So they do not get used”. This physical limitation is compounded by infrastructural deficits, as PHYS-1 points out that advanced algorithms are incompatible with current connectivity infrastructure, noting that staff still struggle with “wireless dead spots in the basement”. Beyond these qualitative deficiencies, JUN-1 identifies a simple quantitative shortage of devices as a primary bottleneck, stating simply: “There were too few mobile PCs for the staff”.

This gap extends to the computational backend, creating a risk that high-potential software investments become *stranded assets*, resources that cannot generate a return because the necessary infrastructure to operate them is absent. Even from a governance perspective, MGMT-2 acknowledges that the specific hardware requirements for advanced AI applications are currently unmet, admitting: “We do not have enough CPU, RAM, or GPU power in stock”. Furthermore, the lack of interoperability forces highly qualified staff to perform manual data entry, bridging the gap between disconnected systems. As PHYS-1 criticises, “the ambulance service sends data digitally, but we often still have to type it in”.

Figure 1 visualises this structural disconnect, illustrating how the theoretical potential of AI (Level 3) is negated by the physical unavailability of access points and computing power (Levels 1 & 2).

**Figure 1**

*The Infrastructure Gap: A Resource-Based View*




*Note.* The pyramid depicts the dependency of AI capabilities (intangible assets) on basic infrastructure (tangible assets). The lack of foundational resources creates an infrastructure-capability gap, blocking strategic AI realisation.

### *4.2 Perception and Acceptance: The Utility-Usability Paradox*

In the context of this MFW, the term paradox is used to denote an analytical tension between perceived usefulness and perceived ease of use, rather than logical contradiction.

Applying the TAM, the analysis reveals a striking dichotomy between the PU and the PEOU of AI systems. While key stakeholders recognise the strategic potential of AI, its practical application is hindered by poor usability, creating a *utility-usability paradox*.

The perception of usefulness is rated highly by management and medical staff (*Median (Mdn)* = 4.0 – 4.5), driven by distinct value propositions. For medical staff, AI is primarily seen as a mechanism for administrative relief and risk reduction. PHYS-1 highlights the potential to alleviate the pressure of "drowning in administrative tasks", viewing AI as a necessary tool to manage increasing documentation workloads. Similarly, junior staff members regard AI as a critical "safety net". JUN-2 describes the technology as a "backup" that validates clinical decisions when supervisors are unavailable, ensuring "that you are simply protected". This operational optimism is mirrored at the strategic level, where MGMT-2 rates the usefulness with a maximum score of 5, driven by the vision of overarching efficiency gains. Notably, the nursing staff remains more sceptical regarding the utility (*Mdn* = 2.5), reflecting a focus on patient-centric rather than administrative tasks.

In sharp contrast to the high strategic expectations, the PEOU poses a significant barrier, particularly for management and nursing staff, who both rate its usability low (*Mdn* = 2.5). Even physicians, who see high utility, rate usability only moderately (*Mdn* = 3.5). The analysis identifies a high data entry burden as the primary obstacle. PHYS-1 warns that the utility of any system collapses if "feeding" the AI requires more time than the cognitive process of triage itself, criticising the necessity of "data entry orgies". This friction is quantified by NURS-2, who illustrates how a recently introduced digital ticketing system increased the workload by requiring "4 - 5 more clicks" compared to the previous analogue process. Consequently, the user experience is characterised by frustration, as PHYS-1 notes that software often feels as if it were developed by "programmers who have never seen a real emergency".

This discrepancy creates a paradox: The staff possesses a high intention to use AI (high PU), but the prohibitive effort required to operate the systems (low PEOU) acts as a deterrent. As visualised in Figure 2, this paradox is most visible in the contrast between management, who focus on the strategic output of efficiency (high PU, *Mdn* = 4.5), and the nursing staff, who struggle with the operational input of usability (low PEOU, *Mdn* = 2.5).

**Figure 2**

*The Utility-Usability Paradox (Triangulation Heatmap)*

| Professional Group | Perceived Usefulness | Ease of Use |
|---|---|---|
| Management | 4.5 | 2.5 |
| Physicians | 4.0 | 3.5 |
| Nursing Staff | 2.5 | 2.5 |
| Medical Students | 4.0 | 4.0 |

*Note.* Values represent median ratings on a 5-point likert-type scale (1 = very low, 5 = very high). Colours indicate high strategic value (green) versus operational barriers (orange/red).

### *4.3 Governance and Participation: The Strategic-Operational Perception Gap*

A critical finding of the analysis is the significant discrepancy in how the governance of AI implementation is perceived across hierarchical levels. While management describes a structured and inclusive process, operational staff report a near-total exclusion from decision-making. This phenomenon, identified here as the *strategic-operational perception gap*, poses a substantial risk to implementation success, as strategic intent fails to translate into operational buy-in.

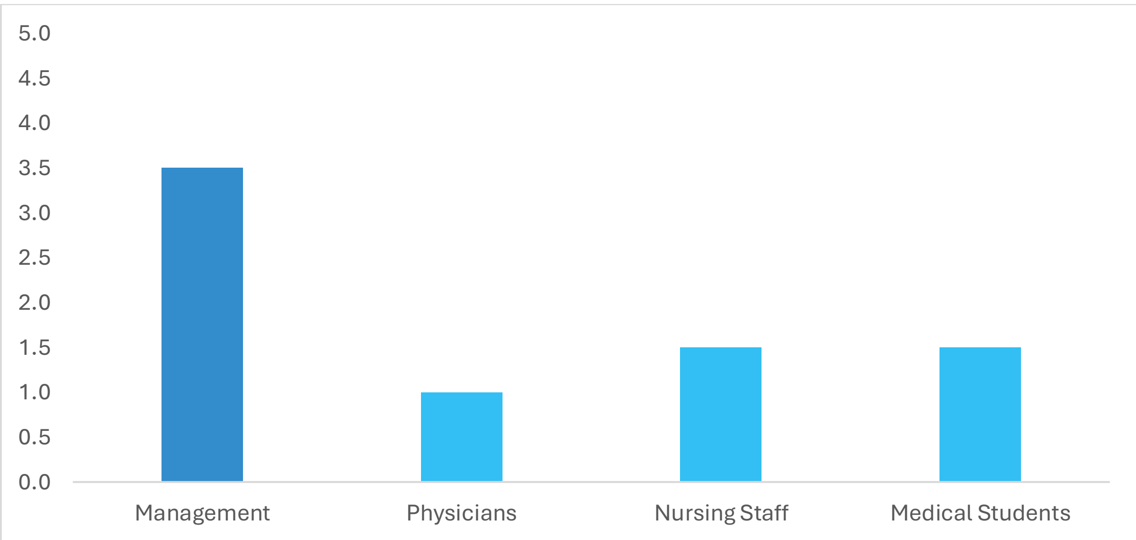
From a management perspective, the introduction of digital tools is viewed as a formally managed, participatory process, resulting in a median participation score of 3.5. MGMT-2 rates the level of participation as high (Score: 4), referencing the establishment of expert councils and strategic workshops mandated by the "Hospital Future Act" (KHZG). He emphasises that the digital strategy was developed collaboratively, stating: "We held a workshop to set up the projects... involving nursing staff, physicians, management, and IT". While MGMT-1 assesses the involvement slightly more cautiously (Score: 3), the overarching perception at the leadership level remains that end-users are adequately represented through institutionalised committees.

In sharp contrast, the operational staff reports a perceived systemic exclusion. This is most visible among the physicians, who unanimously rate their involvement at the absolute minimum, resulting in a median score of 1.0. Even PHYS-2, despite her rank, feels excluded, rating her involvement as a "1". This sentiment is reinforced by PHYS-1, who criticises decisions being made "at the green table in the administration", with end-users often being informed only after systems have been purchased. Similarly, nursing staff and medical students perceive their influence as marginal (*Mdn* = 1.5). NURS-1 notes that technological innovations are imposed without prior consultation regarding their practicality. This exclusion appears to follow hierarchical lines: JUN-2 clearly states that, as a junior staff member "at the very bottom of the hierarchy", there is no mechanism to provide feedback.

Figure 3 visualises this perception gap, contrasting management's positive assessment (*Mdn* = 3.5) with the operational staff's experience of exclusion (*Mdn* = 1.0 – 1.5). This quantitative disconnect suggests that while governance structures exist on paper, they fail to permeate the operational reality.

**Figure 3**

*The Governance Perception Gap*




*Note.* Bars represent median ratings of perceived involvement in decision-making on a 5-point likert-type scale (1 = not involved at all, 5 = strongly involved)

### *4.4 Dynamic Capabilities: Informal Adaptation and Competence Erosion*

From the DC's perspective, an organisation's ability to reconfigure its resources depends heavily on the adaptability of its workforce and the effectiveness of its knowledge transfer mechanisms. The analysis reveals a strong contrast between the organisation's perceived and actual adaptability, leading to reliance on informal shadow learning and a long-term risk of competence erosion. Rather than representing deviant behaviour, shadow learning emerges as a functional adaptation to organisational constraints, compensating for the absence of timely and practice-oriented formal training structures.

*The Adaptability Disconnect*

Quantitatively, there is a distinct divergence regarding the workforce's agility. Management tends to view staff's adaptability sceptically, resulting in a lower median score of 2.5. MGMT-1 rates adaptability as low (Score 2), indicating cultural resistance to change. In direct contradiction, the operational staff perceives their teams as significantly more agile. Physicians rate their team's adaptability consistently high (*Mdn* = 4.0), while nursing staff and students assess it as moderate to high (*Mdn* = 3.5). JUN-2 explicitly rejects the management's scepticism, stating that "everyone in the emergency room is open to new things". She argues that perceived resistance is not due to a lack of willingness but is a rational response to time pressure and dysfunctional infrastructure.

*The Failure of Formal Learning Mechanisms*

Despite this high willingness to adapt, the organisation's formal mechanisms for integrating and building competencies (Teece et al., 1997) are described as largely dysfunctional. The analysis identifies a training gap where institutional support fails to meet operational needs. JUN-1 criticises the timing of educational measures, noting that training sessions often take place "one to two months before implementation", leading to knowledge decay before the actual go-live. Furthermore, PHYS-2 reports a vacuum of professional IT support, forcing medical staff to take over technical onboarding: "Currently, I often help with IT training myself, which is not actually my job".

*Resilience Through Shadow Learning*

To compensate for these structural deficiencies, the staff has developed informal coping mechanisms, identified here as *shadow learning*. NURS-1 describes this as a "snowball system", where knowledge is passed peer-to-peer rather than through institutional channels. Similarly, PHYS-1 notes that the actual exchange of critical knowledge happens via "hallway talks", where workarounds for software bugs are shared during breaks. While MGMT-2 refers to a formal key-user concept, JUN-1's reality shows that these key users are often not released from their regular duties ("so busy with their regular job"), rendering the formal concept ineffective in practice.

*Strategic Risk: Erosion of the Knowledge Base*

A critical inductive finding is the emerging threat of deskilling, the erosion of human expertise due to an over-reliance on algorithmic decision support. Senior supervisors predominantly express this concern. PHYS-1 warns of the danger that young physicians might "lose the clinical gaze" if they rely solely on AI suggestions. PHYS-2 shares this concern, fearing that "junior doctors no longer develop their own expertise" if they bypass the cognitive struggle of diagnosis. This tension is implicitly confirmed by junior staff: JUN-2 views AI primarily as a "safety net" to compensate for a lack of experience. From a strategic perspective, this suggests that while AI may augment performance in the short term, it risks hollowing out the organisation's core intellectual capital in the long term.

## *4.5 Trust, Liability and Ethical Implications*

In a high-stakes environment like emergency care, trust in technology is not merely a preference but a prerequisite for adoption. The analysis identifies legal uncertainty (liability) and the transparency of algorithmic decisions (explainability) as the decisive factors determining whether AI is embraced or rejected.

*The Liability Gap*

A profound *liability gap* emerges between the strategic and individual levels. For management, liability is primarily a regulatory and economic risk. MGMT-1 identifies a lack of a clear legal framework as a barrier to implementation, and questions who is accountable in the event of an AI error: "Is the junior doctor liable or the developer"? Without clear answers, management adopts a defensive stance. For the operational staff, particularly junior physicians, this uncertainty translates into personal, existential fear. JUN-2 expresses deep vulnerability, asking, “Who is liable if I, as a junior physician, rely on this information”? Due to their position at the bottom of the hierarchy, they fear being held personally responsible for algorithmic errors they lack the experience to detect. PHYS-1 reinforces this concern with the drastic metaphor of standing “with one foot in jail” if an error is overlooked. Consequently, he demands that manufacturers “share the burden of risk”, arguing that trust will only be established if vendors share the liability.

*Explainability as an Ethical Imperative*

Given these risks, explainable AI (XAI) is rated as critically important across all groups (*Mdn* = 5.0). It serves not only as a mechanism for validation but also as an ethical necessity for the doctor-patient relationship. PHYS-1 argues that he cannot medically justify a “black box” decision (“I cannot justify this medically if the decision-making process cannot be traced”). For JUN-2, XAI is essential to maintain patient trust; “patients must not feel like the doctor is only relying on the computer”.

*Data Ethics and Bias*

Beyond liability, the interviewees demonstrate a high level of awareness regarding data ethics. NURS-2 highlights the risk of historical bias in training data, noting that “in the past research was primarily conducted on men... textbooks were based on this”. Similarly, MGMT-2 warns of hallucinations in generative AI, emphasising that without deep AI literacy, users might inadvertently accept fabricated diagnoses. This underscores that ethical risks are perceived not just as abstract concepts, but as operational dangers to patient safety.

In essence, the findings suggest that in digital healthcare settings, competitive advantage emerges less from the sophistication of individual technologies than from the organizations`s ability to bundle them with basic, reliable infrastructural resources.

# 5. Discussion

This MFW examined the strategic implications of adopting AI-based DSS in emergency triage and investigated how hospitals can align technological innovation with organisational capabilities. The qualitative analysis revealed profound discrepancies between strategic ambition and operational reality. Subsequently, the findings are interpreted in relation to the theoretical perspectives and prior research introduced in the literature review, before deriving implications for the literature and practical recommendations.

### *5.1 Discussion of the Findings*

This chapter interprets the empirical findings by triangulating the identified themes with the theoretical frameworks and literature introduced in Chapter 2. The analysis reveals that the strategic implications of AI adoption in emergency triage are shaped by complex tensions between technological ambition and organisational reality. These tensions are discussed below through the lenses of the RBV, the TAM, and DC.

**The infrastructure-capability gap as a barrier to value creation.** The empirical identification of an infrastructure-capability gap offers a critical perspective on the application of the RBV in digital healthcare. While the literature posits that digital technologies can serve as strategic resources when they are valuable, rare, and inimitable, the findings demonstrate that the fourth criterion of the VRIO framework “organised,” is the primary stumbling block for value creation. Specifically, the findings show that while the organisation possesses the intangible asset of a strategic AI vision, it fails to bundle this with necessary “tangible assets” such as functional mobile devices, reliable Wi-Fi, and computing power.

This failure empirically illustrates what Sirmon et al. (2007) define as ineffective resource bundling. In their resource management framework, strategic assets create value only when effectively bundled with complementary operational resources. The identified gap confirms that the hospital’s inability to bundle the AI software with basic connectivity infrastructure prevents the formation of a true capability, turning advanced algorithms into stranded assets. Consequently, in the context of emergency medicine, competitive advantage is not derived from the AI technology itself, but from the organisation’s basic digital hygiene. Without this foundation, the value and rarity of AI algorithms cannot be exploited, confirming that resource characteristics alone do not guarantee advantage without institutional congruence.

**The utility-usability paradox is hindering acceptance.** The utility-usability paradox identified in the findings adds nuance to the TAM within high-velocity environments. Davis (1989) establishes PU and PEOU as the dual pillars of acceptance. The findings confirm these factors are critical but reveal a distinct hierarchy in emergency settings. While the literature suggests AI can reduce cognitive burden and standardise decision-making, the empirical reality shows that high data-entry burdens effectively negate these benefits.

This creates a conflict where the theoretical PU (efficiency, safety net) is high, but the PEOU is prohibitively low due to poor software ergonomics. This observation supports the distinction between mere system usage and value realisation proposed by Burton-Jones and Grange (2013). Their concept of effective use suggests that user interaction must be aligned with task goals to create value. This MFW reveals that the high data entry burden forces a trade-off in which the effort required to use the system cannibalises the cognitive resources needed for the actual triage task. Thus, poor usability does not just lower satisfaction; it actively blocks effective use despite high perceived utility. This implies that without seamless integration, the strategic goal of efficiency remains unattainable.

**Governance and the strategic-operational perception gap**. The strategic-operational perception gap regarding governance highlights a failure to align organisational goals with user engagement. The findings reveal a systemic exclusion of operational staff from decision-making, described as decisions made “at the green table”. This disconnect resonates strongly with the findings of Edmondson et al. (2001) regarding the framing of new technology. They demonstrate that successful adoption requires a collective team-learning process, whereas failure often results from viewing the innovation merely as a plug-in technology that fits into existing routines without adaptation.

The observed divergence in participation scores suggests that the organisation implicitly adopted such a plug-in frame, thereby failing to trigger the operational micro-processes, such as enrollment and reflection, necessary for clinical acceptance. This exclusion directly impacts trust. The findings show that legal uncertainty regarding liability acts as a massive barrier, particularly for junior staff, mirroring concerns by Tikhomirov et al. (2024) about oversight complexity. Moreover, the participants’ demand for XAI strongly supports Okada et al. (2023), confirming that black box models are ethically unacceptable in high-stakes contexts.

**Adaptability through shadow learning versus formal training**. Finally, the findings regarding shadow learning and competence erosion offer empirical evidence for the DC framework. Teece et al. (1997) define DC as the capacity to reconfigure competencies to respond to changing environments. The findings indicate that the organisation lacks formal mechanisms for this reconfiguration. Consequently, the workforce develops bottom-up dynamic capabilities through shadow learning (peer-to-peer exchange) to maintain operations.

This phenomenon aligns directly with Beane’s (2019) work, which demonstrated that trainees resort to unauthorised, informal practice to gain competence when formal training is decoupled from operational reality. While Beane focused on robotic surgery, this MFW confirms that the exact mechanism applies to AI-based DSS in emergency triage. Whereas this demonstrates resilience, it highlights a gap in organisational readiness. More critically, the findings uncover a strategic risk of deskilling, where junior doctors may lose their clinical gaze by over-relying on AI. This challenges the optimistic view that AI simply complements clinician judgment, suggesting instead that without deliberate pedagogical strategies, AI adoption could inadvertently hollow out the human expertise that remains the core resource of healthcare delivery.

## *5.2 Implications for Literature*

The findings of this MFW contribute to the existing body of literature by extending established management theories to the specific context of high-stakes healthcare environments. The study provides three key theoretical implications regarding resource orchestration, technology acceptance under pressure, and the dynamics of informal learning.

**Refining the RBV for Digital Health**. First, this study nuances the application of the RBV in digital healthcare. While traditional RBV literature emphasises the possession of rare and valuable assets (Barney, 1995) this research highlights that in hospital digitisation, the competitive advantage of rare resources (e.g., advanced AI algorithms) depends entirely on commodity resources (e.g., Wi-Fi, hardware). By empirically identifying the infrastructure-capability gap, this MFW validates Sirmon et al. (2007) resource management framework in a clinical setting. It demonstrates that the strategic failure lies not in the absence of resources, but in the failure of resource bundling. This implies that future research on digital maturity must view the "organised" component of VRIO not merely as a structural variable, but as an active process of bundling intangible software assets with tangible infrastructure.

**Re-evaluating TAM** Second, the study contributes to the TAM by re-evaluating the relationship between PU and PEOU in time-critical environments. While general TAM literature often treats these variables as parallel predictors (Davis, 1989), this MFW suggests that in the emergency department, PEOU functions as a non-negotiable gatekeeper. The observed utility-usability paradox extends the work of Raita et al. (2019) and Burton-Jones and Grange (2013) by showing that even when perceived usefulness is high (e.g., safety net"), low ease of use prevents the transition from "use" to "effective use." This suggests that theoretical models for ED technology adoption should weight usability not just as a satisfaction factor, but as a prerequisite for operational validity.

**Emergent Dynamic Capabilities**. Third, this MFW extends the Dynamic Capabilities framework by providing empirical evidence for bottom-up reconfiguration in the absence of a formal strategy. The identification of shadow learning in AI adoption confirms that Beane's (2019) concept of deviant learning in robotic surgery applies to algorithmic decision support. This generalises the theory that when organisations fail to provide formal reconfiguration mechanisms (Teece et al., 1997), the workforce will autonomously develop informal, often risky, adaptation strategies. Furthermore, by linking this to the risk of deskilling, the study contributes to the critical literature on AI, suggesting that human-in-the-loop systems may paradoxically degrade the very human loop they rely on if not governed by a formal training strategy that preserves the clinical gaze.

## *5.3 Practical Implications*

The following section highlights the practical implications of the research results and proposes actionable strategies for hospital management and policymakers.

**Prioritise basic digital hygiene over Advanced Algorithms.** Before investing in complex AI-based DSS, hospitals must close the infrastructure-capability gap. Management should prioritise modernising "commodity" resources to ensure stable Wi-Fi, functional mobile devices, and seamless interoperability. An AI strategy without a solid hardware foundation is bound to fail. Investments should focus on eliminating wireless dead spots and ensuring that data is transferred digitally from ambulance to hospital systems to avoid manual entry.

**Bridge the Participation Gap through real-world Governance.** To overcome the strategic-operational perception gap, management must move beyond formal expert councils and engage in genuine participatory design. This involves including end-users (nurses, junior doctors) in the procurement process, not just the implementation phase. Shadowing sessions, where IT decision-makers observe a shift in the emergency room, could help align strategic expectations with operational realities.

**Redesign Training: From PowerPoints to Simulation.** The reliance on shadow learning indicates a failure of current training formats. Hospitals should shift from theoretical presentations to simulation-based training (on-the-job training) that mimics the stress and complexity of the emergency room. Furthermore, to mitigate the risk of deskilling, training should explicitly cover when not to use AI, fostering a critical AI literacy that maintains the physician's independent clinical judgment.

**Resolve the Liability Vacuum.** To foster trust, the liability gap must be addressed. Management needs to establish transparent governance frameworks that clearly define accountability for algorithmic errors. Junior staff must be reassured that they will not be held personally liable for systemic AI failures, provided they follow established protocols. This requires clear standard operating procedures (SOPs) for AI usage.

### *5.4 Future Research and Limitations*

The findings underscore several promising directions for future research. First, the current MFW is based on a qualitative analysis of a single organisation. While this allowed for deep insights into the specific dynamics of the infrastructure-capability gap, it limits generalizability. Future research could apply quantitative methods to survey a larger sample of hospitals to test the prevalence of the utility-usability paradox across the German healthcare system.

Secondly, the phenomenon of shadow learning and deskilling warrants further investigation. Longitudinal studies could examine how the clinical competence of junior doctors evolves in AI-saturated environments compared to traditional settings. This would provide valuable data on the long-term cognitive impact of DSS.

Thirdly, the MFW focused on the internal organisational perspective. Future research should include the patient perspective to understand how patient trust in AI-supported triage influences the doctor-patient relationship.

Certain limitations must be acknowledged. The sample size (N = 8) is small and, with only two participants per stakeholder group, does not support a strict claim of thematic saturation. The sample was instead designed to achieve sufficient *information power* (Malterud et al., 2016) through a specific research aim, purposive expert selection, and a theory-driven analysis. Still, the limited number of participants per group constrains within-group comparisons and should be considered when interpreting the findings. The findings may be influenced by the specific digital maturity level of the case hospital, which achieved a score of 50 in the 2024 Digital Radar Krankenhaus assessment. This score is above the national average of 42.4 on a scale of 0 - 100 (0 = not digitised; 100 = fully digitised) (Amelung et al., 2025). Therefore, the findings may differ in institutions that are at a different stage of their digital transformation. Additionally, as with all qualitative interview studies, the results are based on subjective self-reporting, which may be biased (e.g., social desirability bias in management responses vs. frustration bias in operational staff responses).

Despite these limitations, this MFW provides a comprehensive framework for understanding the strategic challenges of AI adoption, highlighting that successful implementation is less about the technology itself and more about the organisational soil in which it is planted.

# 6. Conclusion

This MFW explored the strategic implications of adopting AI-based DSS in emergency triage. Through a multi-perspective analysis involving hospital executives, physicians, nursing staff, and medical students, the MFW reveals a fundamental disconnect between organisational ambition and operational readiness. The findings demonstrate that an infrastructure-capability gap currently constrains AI's potential to create a competitive advantage. Specifically, without the foundation of basic digital hygiene and connectivity, advanced algorithmic assets risk becoming stranded assets that fail to generate value.

Furthermore, the analysis exposed that successful adoption is not merely a technological challenge but a socio-technical one, constrained by the utility-usability paradox. While the strategic utility of AI is recognised, its practical application is undermined by a high data-entry burden that conflicts with the high-velocity demands of emergency care. This friction is exacerbated by a strategic-operational perception gap, where the exclusion of frontline staff from governance fosters reliance on informal shadow learning, posing a long-term risk of deskilling and competence erosion.

In conclusion, aligning technological innovation with organisational goals requires a paradigm shift from a technology-first to a capability-first strategy. Hospitals must prioritise the modernisation of tangible infrastructure and establish participatory governance structures that bridge the divide between administrative strategy and clinical reality. Ultimately, sustainable value creation through AI depends less on the sophistication of algorithms than on cultivating an organisational environment that harmonises digital tools with human expertise to ensure patient safety and operational resilience.

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# Appendix

## Appendix A: Matrix of Interview Protocols and Theoretical Mapping

| Category / Theme | Emergency Nurses | Emergency Room Doctors | Prospective Doctors | Hospital Management | Theoretical Basis (Inferred/ Explicit) |
|---|---|---|---|---|---|
| Objective | Capture perceptions, expectations, learning, and acceptance patterns of nurses regarding AI-DSS. | Capture perceptions, expectations, learning, and acceptance patterns of ER doctors regarding AI-DSS. | Capture perceptions, expectations, learning, and acceptance patterns of prospective doctors regarding AI-DSS. | Capture the perspective of management on strategic, organizational, and governance implications of AI-DSS. | Resource-Based View (RBV) Dynamic Capabilities (DC) Technology Acceptance Model (TAM) |
| 1. Introduction & Background | | | | | |
| *1.1 Role & Responsibilities* | Can you briefly describe your role and responsibilities in the emergency room? | | | | |
| 2. Perception & Acceptance | | | | | TAM |
| *2.1 Expectations* | What are your general expectations regarding the use of AI systems in the emergency department? | | | | TAM |
| *2.2 Areas of Support* | In which areas do you think AI could best support your work (e.g., triage, diagnostics)? | | | In which areas do you think AI could best support work in the emergency department (e.g., triage, diagnostics)? | TAM |
| *2.3 Usefulness* | How would you evaluate the usefulness of such systems in your clinical routine? (Scale 1-5 ) | | | How would you evaluate the usefulness of such systems or the clinical and organisational processes at your institution? (Scale 1-5) | TAM |
| *2.4 Ease of Use* | How would you assess the ease of use of digital tools you have worked with so far? (Scale 1-5) | | | How would you assess the ease of use of digital tools used in your organisation for medical staff? (Scale 1-5) | TAM |
| *2.5 Influencing Factors* | What factors would influence your willingness to use an AI-supported system regularly? | | | What factors would influence the willingness of doctors and nurses to use an AI-supported system regularly? | TAM |
| *2.6 Explainability* | How important is the traceability or explainability of AI decisions to you? (Scale 1-5) | | | | TAM |
| 3. Org. Integration & Resources | | | | | RBV |
| *3.1 Resources* | What organizational or technical resources do you consider necessary (e.g., IT, training)? | | | | RBV |
| *3.2 Prerequisites* | To what extent does your institution already have the prerequisites to use AI- systems effectively? | | | | RBV |
| *3.3 Involvement* | How involved do you feel in decision-making processes regarding new technologies? (Scale 1-5) | | | To what extent are doctors and nurses involved in decision-making processes regarding new technologies? (Scale 1-5) | RBV |
| *3.4 Support Role* | What role does support from hospital management or IT departments play in successful implementation? | | | | RBV |
| 4. Adaptability (Dynamic Capabilities) | | | | | DC |
| *4.1 Team Adaptability* | How would you assess your team's ability to adapt to new technologies? (Scale 1-5) | | | How would you assess the ability of your doctors and nurses to adapt to new technologies? (Scale 1-5) | DC |
| *4.2 Knowledge Sharing* | How is knowledge and experience about new digital tools typically shared within your work environment? | | | | DC |
| *4.3 Change Example* | Can you describe an example where a technological change was implemented successfully (or less successfully)? | | | | DC |
| *4.4 Competencies* | What competencies or training measures would you find helpful? | | | What competencies or training measures do you consider necessary for doctors and nurses? | DC |
| 5. Strategic & Ethical | | | | | RBV / TAM |
| *5.1 Strategic Contribution* | To what extent do you view the use of AI systems as contributing to the long-term strategic development? (Scale 1-5) | | | | RBV (Strategic Assets) |
| *5.2 Risks & Ethics* | What risks or ethical concerns do you associate with AI in clinical decision-making (e.g., bias, trust)? | | | | TAM (Trust / Risk) |
| *5.3 Acceptance* | In your opinion, what would be necessary for AI systems to gain lasting acceptance and trust? | | | | TAM (Acceptance) |
| 6. Conclusion | | | | | |
| *6.1 Additional Aspects* | Are there any additional aspects or experiences that you consider particularly important? | | | | |
| *6.2 Advice* | If you could give advice to decision-makers or developers of such systems, what would it be? | | | | |

# Appendix B: Coding Manual for MAXQDA

| Code (Level 1) | Code (Level 2) | Code (Level 3) | Definition | Coding Rules | Anchor Examples (Translated) |
|---|---|---|---|---|---|
| 1. Technology Acceptance | 1.1 Perceived Usefulness | *1.1.1 Administrative Usefulness* | Statements regarding efficiency gains in bureaucratic tasks, documentation, coding, or discharge management. | Include: Time savings in writing letters, automated coding, billing support.<br><br>Exclude: Medical decision support (code at 1.1.2). | “My biggest hope is relief. We are drowning in administrative tasks.” |
| | | *1.1.2 Clinical Usefulness* | Statements regarding medical decision support, diagnostic accuracy, triage, or patient safety. | Include: Second opinions, detecting rare diseases, triage prioritization, “safety net.”<br><br>Exclude: Purely administrative time savings (see 1.1.1). | “...security, perhaps an increase in diagnostic certainty, that one is simply protected and does not always have to ask a colleague immediately...” |
| | 1.2 Perceived Ease of Use | | Statements regarding the usability, user interface, intuitiveness, and handling of the system. | Include: Layout, number of clicks, intuitive design, software ergonomics.<br><br>Exclude: Physical hardware issues (see 2.1). | “The software we have is often unnecessarily complicated. Many clicks for simple info.” |
| | 1.3 Data Entry Burden | | Statements regarding the manual effort required to input data, acting as a barrier to usage. | Include: “Feeding” the AI, double documentation, typing data from monitors.<br><br>Exclude: General usability issues not related to input workload. | “If I have to input the information first for an AI to evaluate how sick someone is, I lose a lot of time.” |
| | 1.4 Demographics & Attitude | | Statements regarding the influence of age, experience level, or professional generation on technology acceptance. | Include: Generational differences (young vs. old), digital natives, general skepticism. | “We are a large team... Some are open to it, others are not. [...] I would say: neutral.” |
| 2. Resources & Infrastructure | 2.1 Technical Infrastructure | *2.1.1 Hard- & Software Infrastructure* | Statements regarding the availability and quality of physical devices and network connectivity. | Include: Wi-Fi/WLAN coverage, dead spots, mobile devices (tablets), battery life, server capacity.<br><br>Exclude: Software bugs (see 1.2), Interface issues (see 2.2). | “...we often still struggle with wireless dead spots in the basement or outdated PCs that take ages to boot up.” |
| | | *2.1.2 IT Support & Maintenance* | Statements regarding the availability of technical help and ongoing system maintenance. | Include: Hotline availability, response times, 24/7 support for night shifts.<br><br>Exclude: Initial training (see 3.1). | “Moreover, when problems occurred, it took a long time for IT support to help.” |
| | 2.2 Interoperability (Interfaces) | | Statements regarding the connectivity between different systems and the flow of data across boundaries. | Include: Interfaces between ambulance/ rescue services and hospital systems, media disruptions (paper to digital). | “The rescue service sends data digitally, but we often still have to type it out.” |
| | 2.3 Data Quality & Availability | *2.3.1 Digitization Level (Availability)* | Statements regarding the extent to which patient data is available digitally vs. on paper. | Include: Handwriting vs. digital records, scanning processes.<br><br>Exclude: Quality of the data content (see 2.3.2). | “We still have a lot of information on paper that an AI cannot even take into account.” |
| | | *2.3.2 Data Quality & Ethics* | Statements regarding concerns about bias, representativeness, or the cleanliness of training data. | Include: Gender/Demographic bias, hallucinations due to bad data, nontransparent training sets. | “The selection of training data is nontransparent. One relies on the companies choosing the training data well, so that no prejudices are included.” |
| | 2.4 Financial Resources | | Statements regarding costs, licensing fees, or budget constraints. | Include: Too expensive, missing licenses, budget for hardware.<br><br>Exclude: General economic strategy. | “...but additional useful features are not purchased because the licenses are too expensive.” |

| Code (Level1) | Code (Level 2) | Code (Level 3) | Definition | Coding Rules | Anchor Examples (Translated) |
|---|---|---|---|---|---|
| 3. Dynamic Capabilities | 3.1 Knowledge & Training | | Statements regarding formal mechanisms for learning provided by the organization. | Include: Workshops, simulation training, tutorials, role of key users.<br><br>Exclude: Informal peer-learning (see 3.2). | “There were training sessions, but these often took place one to two months before the actual introduction.” |
| | 3.2 Informal Knowledge Transfer | | Statements regarding unstructured, social learning processes outside of formal channels. | Include: Office grapevine, peer-to-peer help, learning by doing, asking colleagues during breaks. | “The real exchange happens informally classic, office grapevine.” |
| | 3.3 Process Adaptation | | Statements regarding routines and workflows that change (or need to change) to accommodate AI. | Include: Changes in patient paths, shifting roles, definition of new SOPs | “I have to define processes: In which cases is the resident allowed to use AI for decision support?” |
| 4. Governance, Ethics & Risks | 4.1 Liability & Accountability | | Statements regarding legal responsibility and accountability in case of errors. | Include: Accountability (doctor vs. AI vs. manufacturer), legal certainty, fear of litigation.<br><br>Exclude: General ethical concerns without legal context. | “Is the resident liable? Or the developer or manufacturer of the AI? [...] If I don't know that, I won't rely on it.” |
| | 4.2 Professional Identity & Deskilling | *4.2.1 Role Conflict (Identity)* | Statements regarding tensions between human authority and AI recommendations, or the patient relationship. | Include: Patient trust, doctor vs. computer, fear of being replaced/devalued. | “The patient must be able to trust the doctor and not have the feeling that the doctor only listens to the PC.” |
| | | *4.2.2 Deskilling (Competence)* | Statements regarding the loss of human expertise due to over-reliance on technology. | Include: Loss of clinical gaze, residents not learning manual diagnostics, blind trust acting as a crutch. | “I see the danger of 'de-skilling'. If young doctors only rely on the machine's suggestions, they might unlearn the clinical gaze.” |
| | 4.3 Trust & Explainability | | Statements regarding the transparency of algorithms and the resulting user trust. | Include: Black Box problem, need for explainable parameters (XAI), verification of results.<br><br>Exclude: General trust in colleagues. | “A 'Black Box' that just spits out a result is something I cannot justify medically.” |
| | 4.4 Strategic Alignment & Participation | *4.4.1 Strategic Vision* | Statements regarding the definition of long-term organizational goals by management. | Include: Efficiency goals, competitive advantage, digital target picture, management vision.<br><br>Exclude: Operational details. | “Basically, management must have a digital target picture and make a decision: What strategic goal am I pursuing?” |
| | | *4.4.2 Participation & Change Management* | Statements regarding the involvement of operational staff in decision-making processes. | Include: Surveys, workshops, feedback loops, feeling of exclusion (green table decisions). | “Such things are usually decided at the 'green table' in the administration... We users are often only informed when the system is already purchased.” |