Bachelor's Thesis: AI as a doctor, an analysis of the influence of AI implementation in the medical field.

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AI use statement

During the preparation of this work the author used **ChatGPT** in order to work out writing structures by analysing existing scientific literature and generating writing structures inspired by said literature. Additionally, ChatGPT was used to develop blocks of code and figuring out errors for data analysis in Rstudio, as it is significantly faster than scouring the internet and StackOverflow for solutions. After using this tool/service, the author reviewed and edited the content as needed. The author takes full responsibility for the content of the publication.

Abstract

Artificial Intelligence (AI) is rapidly entering healthcare, raising questions about its influence on the skills and competencies of medical specialists and considerations for its adoption in clinical settings. Research Question 1 asked: “How do medical specialists perceive the influence of AI on the Skills and Competencies required for their profession?” Research Question 2 asked: “How do perceptions of those Skills and Competencies, expected AI-driven changes to CanMEDS facets, and satisfaction of SDT needs shape willingness to adopt AI?” A sequential exploratory mixed-methods design interviewed 20 Dutch specialists, then surveyed 35 others. The survey measured three independent variables, namely SDT needs (autonomy, competence, relatedness), views Skills & Competencies, and expected AI-driven changes to the seven CanMEDS facets against one dependent variable, willingness to adopt AI, via multiple linear regression. Qualitatively, 5 themes with 12 sub themes emerged with specialists welcoming AI that speeds work but resisting tools that obscure or supplant core knowledge. Quantitatively, stronger views on skills and competences predicted greater willingness to adopt AI ($\beta \approx .05$, $p = .002$). Competence added a small positive effect ($\beta \approx .18$, $p = .013$), while autonomy and relatedness were non-significant. Expecting AI to change many CanMEDS facets did not predict willingness to adopt AI, although anticipating alterations to the Knowledge/Science facet specifically decreased it ($\beta \approx -.62$, $p = .009$). Adoption depends less on generic tech optimism than on **“**Capability Assurance,” the requirement that AI will support rather than erode specialist’s ability to practise safely and capably. Implementations that preserve decision autonomy, make algorithmic reasoning transparent, and frame AI as a skill extender are most likely to gain specialist trust. Therefore, future work could validate the custom Skills and Competencies scale and test capability assurance in larger, multi-centre samples.

1. Introduction

The emergence of Artificial Intelligence tools such as ChatGPT and Deepseek in the last couple of years has been a development, offering many new opportunities for the advancement of technology and humanity. For example, ChatGPT is currently the top charting application in the Apple App Store above TikTok and other social media platforms, with millions of users worldwide utilising these type’s LLMs for information acquisition, image generation and even to write essays. Similarly, AI is being used in medical equipment such as EEGs to aid in detecting and predicting brain disorders (Shang et al., 2024)

Artificial Intelligence (AI) refers to systems designed to perform tasks that typically require human intelligence, such as learning, reasoning, and decision-making (Krafft et al., 2020; Wang, 2019). Although there is no single, universally accepted definition of AI, the field encompasses a range of perspectives, from technical descriptions focusing on algorithms and system functionalities to broader societal and ethical considerations emphasizing human-like traits (Krafft et al., 2020; Wang, 2019). Fundamentally, AI works by processing data through algorithms to recognize patterns, make predictions, or take autonomous actions aligned with specified objectives (Krafft et al., 2020). These systems can range from simple rule-based models to complex deep learning architectures capable of adapting and improving over time. Exploring AI and how it influences human behaviour such as job performance is important for assessing its applications, particularly in sensitive areas like healthcare, where AI’s ability to analyze vast datasets and support decision-making could possibly have a significant impact on outcomes.

AI technologies are increasingly being applied in various domains of healthcare, demonstrating potential in both clinical and operational settings. In clinical diagnostics, AI systems using deep learning have outperformed human specialists in tasks such as detecting early-stage breast cancer, classifying skin lesions, and identifying pneumonia in chest X-rays with high sensitivity and specificity (Alowais et al., 2023). In cardiology and neurology, AI has aided in interpreting ECGs, predicting stroke outcomes, and managing chronic diseases through outcome prediction and treatment optimization (Jiang et al., 2017). AI also contributes to administrative efficiency, for example by optimizing logistics and inventory using predictive algorithms, enhancing patient scheduling, and supporting clinical decision-making with real-time data insights from electronic health records (Jiang et al., 2017). Virtual health assistants and chatbots are used to triage symptoms, provide patient education, and support elderly or chronically ill individuals with daily healthcare needs (Alowais et al., 2023). These developments reflect a rapid expansion of AI across diverse aspects of healthcare, from diagnostics to patient support and system management while clarity of the impact of AI on the performance of healthcare specialists is still being explored.

1.1 Skills and Competencies in Healthcare

Across medical specialties, core competencies reveal both shared principles and specific skills that align with the demands of individual fields. To elaborate, an example of these specific skills can be found in internal medicine, as defined by the Spanish Society of Internal Medicine (SEMI), essential competencies include broader clinical knowledge than the average specialist, patient care across healthcare levels, ethical professionalism, communication with multidisciplinary teams, proficiency in diagnostics and procedures, cost-awareness, and academic engagement in teaching and research (Porcel et al., 2012). Another example of this can be be see in the field of urology, according to Morrison and Macneily, which integrates general physician competencies from bodies like the RCPSC and ACGME but places special emphasis on surgical expertise, practice management and collaboration with professionals such as radiologists and pathologists (Morrison & MacNeily, 2004). In contrast, diabetes care lacks a specific competency list but is framed as universally relevant; all healthcare professionals are expected to be competent in prevention, patient-centered diabetes care, interdisciplinary teamwork, and culturally sensitive, evidence-based management, as highlighted by the ADA’s longstanding involvement in shaping educational standards like the 1993 nursing competencies (Childs, 2005).

While the specific competencies may differ according to the demands of each discipline, a shared foundation of core professional capabilities runs consistently across them. According to the comprehensive framework outlined in the healthcare education reform book (Institute of Medicine, 2003), five universal competencies are essential for all health professionals: providing patient-centered care, employing evidence-based practice, working effectively in interdisciplinary teams, applying continuous quality improvement methods, and utilizing informatics to support clinical decisions. These are designed to be embedded in daily clinical practice across specialties. Complementing this, the competency framework (Ten Cate, 2005) emphasizes that true professional competence extends beyond isolated technical tasks to include holistic, integrated capabilities such as ethical judgment, teamwork, communication, and management, all of which are required to safely perform complex clinical activities. These shared competencies, regardless of specialty, enforce that health professionals not only master their discipline-specific skills but also function effectively within an evolving, team-based, and patient-centered healthcare system. Another framework for medical competency is the CanMEDS framework (Frank et al., 2015), which stands for the Canadian Medical Education Directives for specialists. It organizes medical practice around seven interconnected roles: Medical Expert, Communicator, Collaborator, Leader, Health Advocate, Scholar, and Professional. These roles are integrated into many medical education systems worldwide and serve as a foundational blueprint for developing competent, reflective, and adaptable healthcare specialists. A relevant detail for the context of this research is that the Dutch version of the CanMEDS visualisation does not utilize “roles” as much as it depicts different facets of medical professionalism as can be seen in a report on the Framework of the Dutch Medical Education plan from the Nederlandse Federatie van Universitair Medische Centra (2020).

The implementation of AI into clinical practice introduces a complexity in its influence on medical competencies, due to AI offering opportunities for skill enhancement and while causing concerns about professional erosion. On one hand, studies caution that when AI, particularly large language models (LLMs), is positioned as a replacement rather than a support for human judgment, it can erode foundational competencies such as diagnostic reasoning, patient interviewing, and autonomous clinical decision-making (Goh et al., 2024; Agarwal et al., 2024; Alowais et al., 2023). Over-reliance on AI may lead to gradual deskilling, especially when clinical workflows or training frameworks fail to preserve physician interpretive agency and autonomy (Goh et al., 2024; Alowais et al., 2023). Furthermore, concerns are also severe in high-complexity medical contexts, such as oncology or diagnostic imaging, where AI tools often struggle with variability and uncertainty, leading specialists to expend more cognitive effort interpreting outputs (Huo et al., 2025), which could delivering less care due to time losses. In such settings, specialists may question the reliability of AI, especially when its recommendations lack transparency or context sensitivity, which is a common feature of so-called “black box” models (Goh et al., 2024; Huo et al., 2025; Alowais et al., 2023).

Yet, when designed and deployed thoughtfully, AI offers substantial promise for strengthening and extending clinical competencies. AI systems help mitigate human limitations such as information overload, cognitive bias, and diagnostic fatigue, supporting physicians in making more accurate, data-driven decisions (Goh et al., 2024; Agarwal et al., 2024). In fields where speed and complexity converge, such as genomics or oncology, AI enables rapid pattern recognition and the synthesis of large-scale patient data to inform personalized care pathways (Agarwal et al., 2024; Alowais et al., 2023). Routine and administrative burdens can increasingly be offloaded to AI systems, empowering specialists to focus on higher-order diagnostic challenges and patient-centered interactions, which in turn fosters professional autonomy, competence, and psychological satisfaction (Huo et al., 2025; Alowais et al., 2023). This redistribution of effort supports not only more effective care but also informal, experiential learning, where ongoing interaction with AI becomes a vehicle for skill reinforcement and continuous growth (Huo et al., 2025). AI’s possible influence on medical education could large as well: tools such as structured reflection frameworks can deepen diagnostic reasoning, while broader AI literacy in curricula ensures that future specialists develop the ability to evaluate, interpret, and ethically engage with AI outputs (Goh et al., 2024; Alowais et al., 2023). Importantly, when AI is framed not as a replacement for human expertise but as an augmentative collaborator, it promotes human–machine synergy that advances both clinical performance and the professional identity of healthcare providers (Huo et al., 2025; Alowais et al., 2023).

1.2 Willingness to adopt

Willingness to adopt AI in healthcare is shaped by a complex interplay of personal, social, and organizational factors, with trust emerging as a central and recurrent mediator. Across several studies, initial trust in AI systems, whether in their accuracy, reliability, or ease of use, has been shown to strongly predict willingness to engage with them, often more so than direct expectations of performance (Wang & Wang, 2024; Ratta et al., 2025). For instance, doctors who display high trust propensity or perceive a system as user-friendly are significantly more inclined to adopt AI diagnostic tools, regardless of their actual performance benefits (Wang & Wang, 2024). Similarly, trust acts as a crucial bridge between perceived usefulness and actual willingness, meaning that even when healthcare professionals recognize AI’s potential, concerns about safety or opacity can erode their intent to use it (Ratta et al., 2025). Further, embedded biases within AI algorithms can distort judgment, especially when the systems are trained on non-representative data, raising ethical alarms about fairness and safety (Alowais et al., 2023). Resistance to AI adoption, therefore, stems not merely from lack of familiarity, but from deeper professional concerns: fears of diminished clinical authority, eroded judgment, loss of skill relevance, and compromised care quality (Agarwal et al., 2024; Huo et al., 2025; Alowais et al., 2023).

Notably, social influence plays a variable role: while it is a primary driver for medical students, who are influenced by perceived expectations from peers and mentors (Mishra & Upadhyaya, 2024), its effect appears less pronounced among practicing medical specialists in some settings (Ratta et al., 2025), where personal trust and perceived risk hold greater weight. Performance expectancy remains influential but often indirectly, as its impact is frequently filtered through trust-based perceptions of reliability and efficacy (Wang & Wang, 2024; Yu et al., 2025; Ratta et al., 2025). Additionally, personal innovativeness significantly boosts willingness, particularly among doctors in tertiary hospitals, where openness to innovation may substitute for other influencing factors (Yu et al., 2025). In more resource-limited environments, organizational support becomes decisive: the presence of training, technical infrastructure, and a culture that fosters innovation is essential to cultivate adoption (Yu et al., 2025). Collectively, these findings imply that specialists' willingness to adopt AI depend not only on trust and contextual aids but also on whether they feel autonomous in their choice, competent in its use, and supported by their professional community, which are the three basic psychological needs articulated by Self-Determination Theory.

1.3 Self-Determination theory

Self-Determination Theory (SDT) (Ryan & Deci, 2018) is a macro-theory of human motivation that emphasizes the importance of satisfying three fundamental psychological needs, namely autonomy, competence, and relatedness, for optimal psychological functioning, engagement, and well-being. Developed by Deci and Ryan, SDT posits that these needs are universal and essential for fostering intrinsic motivation, regardless of context or individual differences. When individuals perceive their environment as supportive of these needs, they are more likely to be engaged, self-motivated, and experience a sense of well-being. Conversely, environments that thwart these needs can result in disengagement, stress, and resistance to change.

Outside the healthcare context, SDT has been applied to the design of AI-enabled learning tools. For instance, social robots for adult learners that are designed using SDT principles, offering choice, responsiveness, and interactive engagement, have been shown to significantly boost intrinsic motivation and learning outcomes (Lu et al., 2023). Similarly, digital education research shows that mobile learning tools supporting autonomy and competence lead to improved motivation, achievement, and well-being (Jeno et al., 2019). A Large-scale cross-national and longitudinal study (Bergdahl et al., 2023) further reinforces SDT's applicability to AI adoption. Satisfaction of autonomy and relatedness needs has been shown to correlate with more positive attitudes toward AI, greater trust in intelligent systems, and lower resistance to their integration, even in complex or uncertain contexts.

In the context of healthcare, SDT could provide a framework for understanding how professionals behave in the context of integrating AI technologies into their work environment. When AI systems are perceived as tools that enhance rather than replace professional expertise, they can contribute positively to these core psychological needs. For example, AI can support autonomy, the experience of volition and control over one's actions, by enabling medical specialists to make more informed decisions without removing their decision-making power. Similarly, AI can promote competence by supporting accurate diagnostics, offering decision-support tools, and providing relevant feedback that helps professionals refine their skills and stay updated with evolving clinical standards (Huo et al., 2025). Furthermore, Relatedness, the third SDT need which refers to the desire to feel connected to others and to belong is also a facet that can be indirectly supported by AI implementation. In healthcare environments where teamwork and communication are critical, AI systems that support collaboration and communication among healthcare professionals, rather than creating distance between them, are more likely to be accepted and effectively integrated into clinical practice (Bergdahl et al., 2023). Additionally, the use of AI in healthcare has been shown to enhance professionals' work well-being indirectly by satisfying psychological needs such as autonomy and competence, particularly when job complexity is moderate, which for example could be administrative work or mundane tasks. (Huo et al., 2025).

1.4 Current research

This thesis explores the relationship between the Willingness to adopt AI, views on Skills and Competencies for medical specialists and Self Determination Theory. The primary objective is to explore how medical professionals such as doctors, radiologists, and surgeons perceive the influence of AI on their skills and competency, with a secondary objective being how these perceptions shape their willingness to adopt such technologies in practice using SDT as the theoretical guiding framework. The thesis is part of a larger research project from the Saxion IDE lectorate, which aims to develop a guideline for developing and implementing AI in the Dutch Healthcare system.

In order to create a detailed contribution to the guideline for AI implementation, this study utilised a mixed method research design, using a sequential exploratory design. The first part of the study starts off with in depth interviews with medical professionals, guided by Research Question 1.

RQ 1: How do medical specialists perceive the influence of Artificial Intelligence on the needed skills and competencies for their medical profession?

The second part continues with a survey to quantify the information from the interviews and to investigate the secondary research question:

RQ 2: How do perceptions on medical skills and competencies, the expected influence of AI on these skills and Competencies and the satisfaction of the basic psychological needs found in SDT shape healthcare professionals' willingness to adopt AI in clinical settings?

This secondary research question will be answered using 1 hypothesis **(H1)** for testing and 2 for further exploration into the topic (**H2** and **H3**).

H1*: Greater satisfaction of psychological needs (autonomy, competence, and relatedness) is positively associated with intention to adopt AI in clinical practice*.

H2: *Stronger beliefs about core skills and competencies for medical professionals (Skills and Competencies Total score) are associated with greater willingness to adopt AI.*

H3: *Medical professionals who expect AI to alter a larger amount of core facets of medical Skills and Competencies (CanMEDS Facets) are less willing to adopt AI.*

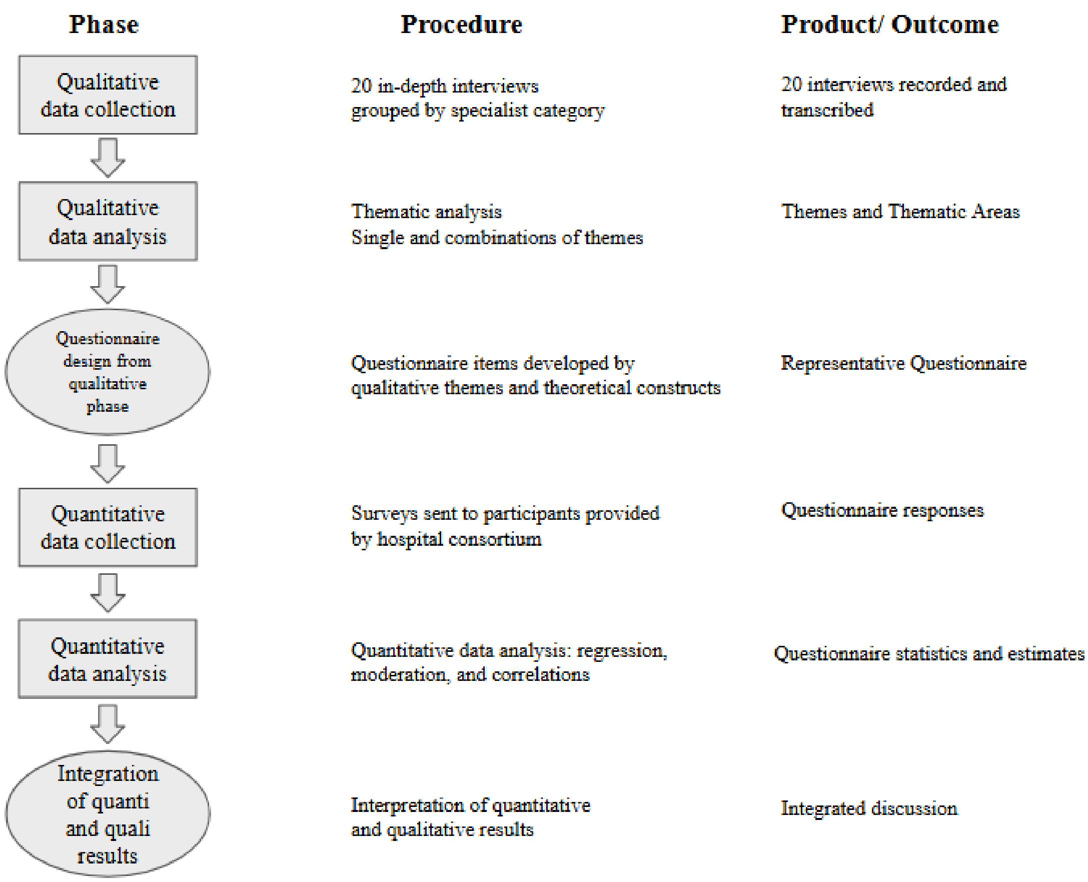
2. Methods

2.1 Study design

This study utilised a mixed-methods approach with an exploratory sequential design, starting with qualitative interviews and followed by survey development, after which a quantitative survey was designed and tested. The qualitative insights aided in the survey construction, after which the quantitative data validated and expanded on the qualitative findings. The data was stored on encrypted university servers and anonymized locally before analysis. Confidentiality and GDPR compliance were maintained throughout. **Figure 1** illustrates how the different phases of the sequential study design were carried out.

Figure 1

Procedure figure for Qualitative and Quantitative Phase



2.2 Qualitative Phase

2.2.1 Participants

A total of 24 medical professionals, of which 20 participated, were approached. The specialists were active in 3 types of hospitals, namely Top-Clinical, Academic and General. Furthermore, the participants' specialisations are categorized in 3 orientations of specialism. The first orientation being cognitive, which focuses on diagnosis and interpretation such as radiologists or neurologists. The second orientation is interventional, which are focused on intervention and treatment such as surgeons or gynecologists. The third orientation is supportive, which focuses on long-term care, patient support and psychosocial aspects of health, like psychiatrists or geriatric specialists.

The participants’ contact information was provided through the consortium of hospitals, after which the researchers at Saxion contacted them through email. They were then informed of the study, and signed informed consent forms before participating in the interviews. Additionally, the participants had to consent before a recording of video and audio was made in teams. The participants were contacted and interviewed from mid december 2024 to late march 2025 with participation being fully voluntary with no additional incentive. The interviews lasted on average 45 to 60 minutes and were conducted either in person or virtually. After the interview, participants were also asked if they wanted to join future focus groups for the development phase. Participants were all practicing medical professionals in the Netherlands, aged between 25 and 65, with 15 males and 5 females. The participants were from 14 specialisations, with the highest frequency being ER Doctor (n = 4) and Radiologist (n = 3). The interviews were conducted in Dutch, either in person or via Microsoft Teams.

2.2.2 Materials and Instruments

An interview protocol was developed based on a literature review by the researchers from Saxion and consultations with domain experts. The semi-structured interviews were divided into three key sections. First, participants were asked about their background and what Skills and Competencies meant to them in their specific medical role. This included questions about core skills and competencies, values, and motivations in their daily work. The second part focused on current experiences with AI in clinical practice, ranging from familiarity and observed use to perceived benefits and limitations. The final section addressed expectations and concerns about AI’s future role, including its potential impact on professional autonomy, work satisfaction, and the evolution of core competencies.

The interviews were exploratory by design, which allowed for flexibility and follow-up questions, and served as the foundation for understanding how AI integration aligns or conflicts with professional identity and clinical expertise. Additionally, an exercise where the professionals ranked core values of skills and Competencies in their medical specialty was performed. The exercise was done twice, once before the AI section of the interview and once after the AI section to investigate the changes in the ranking in case of a hypothetical AI implementation. See **Appendix B** for the ranking exercise developed by the Saxion Researcher that was used in the interviews.

2.2.3 Data Analysis

Interviews were recorded and transcribed using Microsoft Teams or transcription tools such as Amberscript. The transcriptions were then anonymized for analysis. Afterwards, the transcripts were analyzed using Atlas.ti. The coding process followed a combination of inductive and deductive approaches: initial codes were developed based on recurring ideas from the interview data, such as AI related codes about the attitude towards ai or the willingness to adopt AI, while also informed by the earlier knowledge gathered during the project such as predictions for adoption requirements or Self Determination Theory needs. Two researchers independently coded two transcripts each and discussed discrepancies to align interpretations. This process involved two rounds of refinement, resulting in a jointly agreed coding scheme. While interrater reliability was not formally calculated, consistency was ensured through collaborative discussion and consensus. The researchers then applied the final coding scheme to the full dataset. A thematic analysis was conducted to identify recurring patterns in participants' perceptions of skills and competencies for medical professionals, the attitude and views on AI and Self Determination Theory facets. Themes were generated by grouping frequently recurring and similar codes and discussing overarching ideas across interviews. Although a formal saturation check was not conducted, the researchers ensured thematic coherence and richness through iterative coding rounds and regular debriefing. Given the exploratory nature of the study, the process was guided by iterative reflection and close collaboration.

2.3. Quantitative Phase

The quantitative phase consisted of a survey distributed to a broader population of Dutch medical professionals. The survey was designed to quantitatively assess themes identified in the qualitative phase and grounded in the theoretical frameworks of Self-Determination Theory (Ryan & Deci, 2018).

2.3.1 Participants

The survey was distributed to medical professionals via internal communication systems of the consortium hospitals. Inclusion criteria included being a practicing medical professional in the Netherlands. Demographic data such as age, gender, specialization, years of experience, and Perceived AI knowledge were collected. Out of the 76 responses, 35 passed the requirements for data analysis. In order to pass the requirements for analysis, the respondents had to have accepted the informed consent, be a practicing medical specialist and had to have completed the questionnaire. The mean age was 45.4 years old (SD = 11.2), with the youngest being 28 and the oldest being 65 years old. The population was 57.1% male (n = 20) and 42.9% female (n = 15). The groups of specialisms were represented as follows, Supportive (8.6%, n = 3), Observational (31.4%, n = 11), Surgical (45.7%, n = 16), Combined (B/S) (2.9%, n=1) and other/unknown (11.5%, n = 4). The population represents 3 types of hospitals, Academic (34.3%, n = 12), Top-Clinical (54.3%, n = 19) and general (11.4%, n = 4). The work experience was distributed as follows, 0-5 years (14.3%, n = 5), 6-10 years (22.9%, n = 8), 11-15 years (17.1%, n = 6), 16-20 years (11.4%, n = 4) and 20+ years (34.3%, n = 12). Perceived AI knowledge was also tested using a slider scale ranging from 0 to 10 (M = 5.0, SD = 2.9) with the minimum selected being 0 and the maximum selected being 9.

2.3.2 Materials and Instruments

The questionnaire was developed collaboratively by the student researcher, a fellow Saxion researcher, the project supervisor, and discussed in a focus group with representatives from the participating healthcare consortium. Early insights from the qualitative analysis and theoretical foundations from Self Determination Theory formed the foundation of the questionnaire. Response formats included Likert scales, open-ended items, ranking tasks, and interactive components such as the clickable CanMEDS diagram. Feedback was collected through a pilot sent to all consortium members, including an HR specialist previously involved in related research on professionalism in nursing. Feedback focused on clarity and structure, and no substantive changes were deemed necessary following the pilot. The final version of the questionnaire was distributed using Qualtrics. Lastly, not all tested and analysed items of the questionnaire are reported in this report, as Saxion and the consortium of hospitals had interests that were beyond the scope of this thesis.

The survey consisted of multiple sections in the following order: It started off with the first section where informed consent was collected. The second section then collected Demographic information, with the third section testing for current knowledge and use of AI. The fourth section tested for the views on core skills and competences for medical specialists. The fifth section tested for perceived and desired influence of AI on CanMEDS Facets which were operationalized using a clickable CanMEDS figure. The sixth section tested for the adoption of AI, with an item about the willingness to adopt AI and the SDT questions. The seventh section provided contact information from the researchers and asked if they participants wanted to be involved with further participation. The eighth and last section was a small debriefing.

Going into more detail for the questionnaire, the participants first encountered an informed consent page. The survey then continued with an eligibility question to check whether the participant is a medical professional.

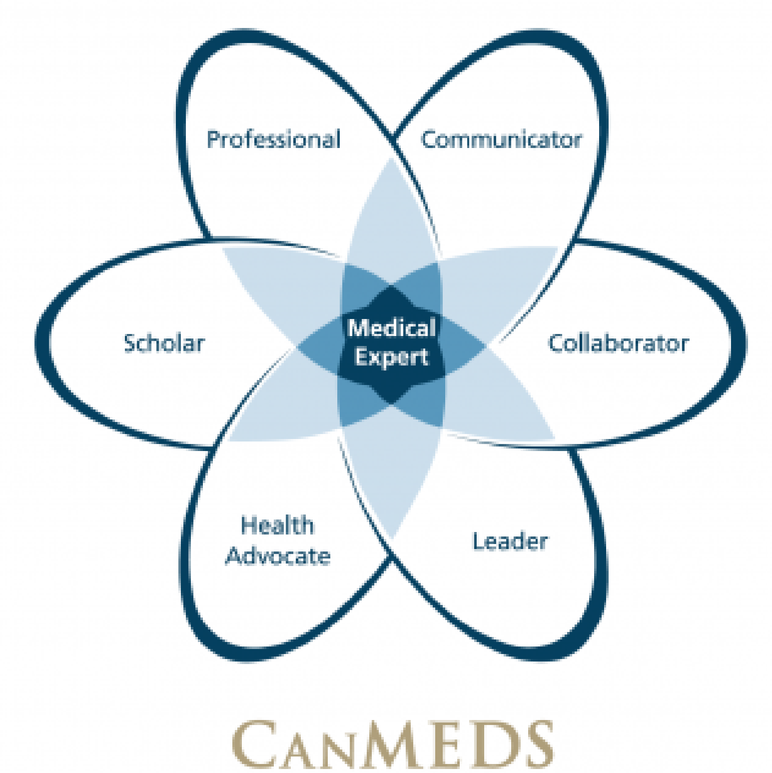
If both the informed consent and the eligibility check were correct the participant then continued to the demographics section. This section asked the participant to clarify their age, gender, specialism within the hospital (*multiple choice*), type of hospital (*academic, top-clinical or general*) the specialist was employed at and the amount of years of work experience the participant had.

The questionnaire then continued to section 3, which entailed the current use and knowledge of AI. This section started off with an item about the perceived knowledge of AI which could be answered using a slider that ranges from 0 to 10. The participants were then asked to give their own definition of AI (*open answer*), which AI tools the participants uses in their personal daily life (*open answer*), which AI tools the participant uses in their daily work life (*open answer*), which phase and what types of AI tools they are involved with (*multiple choice item with open answers for each selected answer: Involved with development, Involved with research, Involved with implementation, none*)

The questionnaire then continued to section 4, starting off with 22 statements (*5 point Likert scale*) about Skills and Competencies, of which the full scale can be found in **Appendix Scale C1**. The scale was inductively developed in collaboration with the saxion researcher, using themes from the qualitative interviews and the ranking exercise **(appendix B)** about skills and competences as a foundation. Afterwards, the participants had to rank, from most important to least important, the 10 Skills and Competencies that were also ranked in the qualitative interviews, with two of the items from the qualitative ranking exercise being replaced due to being too orientation specific.

Section 5 of the questionnaire entailed the perceived and desired change in Skills and Competencies, with participants being presented with a visual representation of the CanMEDS framework, seen in **Figure 2**, as multiple participants already highlighted in the interviews that they were familiar with said framework due to their education. The participants first had to select which facets of the CanMEDS framework they expected to change due to the implementation of AI by clicking on those sections of the CanMEDS framework in the visual representation. The second question was very similar, asking the participant to instead select what they desired to change due to the implementation of AI

Figure 2
The visual representation of the CanMEDS framework



Section 6 of the questionnaire touched on the adoption of AI and the SDT items, with 9 items that were answered using a 5 point likert scale and one multiple choice/ open answer item detailing the requirements for adoption. Given the limited number of items permitted for the SDT section due to time constraints, a custom 7-item subset was constructed based on SDT principles, with an emphasis on the Autonomy and Competence facets. Relatedness was only minimally included, as early qualitative analysis suggested it was largely irrelevant in this context. For the 9 Likert scale items, the first item was a question about the willingness to adopt AI, the next 7 were SDT items of which the scale can be found in **Appendix Scale C2** (3 Questions for Competence with 1 being reverse coded, 3 questions for Autonomy with 1 being reverse coded, 1 question for relatedness as the qualitative interview analyses highlighted that relatedness was not strongly relevant). The last question was a negatively coded item that checked for the influence of AI on the interestingness of the participants' job. The multiple choice/ open answer question asked what was required to successfully adopt AI in the specialists daily work environment, with the options being "Success stories from peers", "Personal successful experiences", "AI training", "Time and Money" and "Other: with an open answer box.

The questionnaire then continued to section 7, asking if the participant wanted to be kept up to date with further developments in the "AI as doctor" project and asking for their email address if so. Lastly, section 8 of the questionnaire contained a small debrief that also contained the contact information of the researchers.

2.3.3 Data Analysis

Survey data collected via Qualtrics was exported to RStudio for analysis. The data was first screened for completeness, cleaned, and re-coded where necessary. Descriptive statistics were calculated for all key variables, including Willingness to adopt AI, the Skills and Competencies total score, the SDT scale (including subscales), and the expected change across CanMEDS facets.

For the CanMEDS items, since they were questions that allowed for multiple selections, the individual possible selections were transformed into columns with binary coding (*1 = the participant selected the facet, 0 = the participant did not select the facet)*. Furthermore, the sum of selected facets was also calculated. This allowed for predictions using both the individual facets and the total amount of selected facets.

Before proceeding to hypothesis testing, it was necessary to assess the reliability and validity of the instruments used. Unlike validated standardized measures, newly constructed or adapted scales require psychometric evaluation to ensure their scores meaningfully reflect underlying constructs. Assessing internal consistency and factorial structure first safeguards against biased or misleading regression results due to poor scale quality. Therefore, both reliability (Cronbach's alpha and McDonald's Omega) and construct validity (via exploratory factor analysis) were examined before conducting further statistical analyses. Assumptions of linear regression were also assessed using diagnostic plots. Linearity, residual assumptions and multicollinearity were tested.

Continuing to the evaluation of the study's hypotheses, the hypotheses were tested using two main stepwise regression models, namely a "full" model including the Skills and Competencies total score, the SDT subscale scores, and individual CanMEDS facets as predictors, on which a stepwise variable selection procedure based on Akaike Information Criterion (AIC) was performed to remove unnecessary variables. Furthermore, a "simple" model with the Skills and Competencies total score, SDT total score (the sum of all the subscale scores), and the sum of perceived CanMEDS changes to directly test the hypotheses, on which a stepwise variable selection procedure based on Akaike Information Criterion (AIC) was also performed to remove unnecessary variables.

Hypothesis 1, which stated that "Greater satisfaction of psychological needs (autonomy, competence, and relatedness) is positively associated with intention to adopt AI in clinical practice", was assessed with the "Simple" multiple linear regression model with the SDT total score (which is the sum of all subscale scores) being the independent variable and Willingness to adopt AI being the dependent variable. Subscales were also analysed with the "Full" model to explore the separate effects of Autonomy, Competence, and Relatedness.

Hypothesis 2, which stated that "Stronger beliefs about core skills and competencies for medical professionals (Skills and Competencies Total score) are associated with greater willingness to adopt AI," was assessed with both the "full" and "simple" multiple linear regression model, as the Skills and

Competencies total score was present in both. Willingness to adopt was again the dependent variable, with the Skills and Competences total score being the independent variable in both regression models.

For hypothesis 3, which stated that “Medical professionals who expect AI to alter a larger amount of core facets of medical Skills and Competencies (CanMEDS Facets) are less willing to adopt AI,” the summed amount of expected CanMEDS changes (from the clickable framework task) in the “simple” multiple linear regression model was used as an independent variable to test whether higher perceived AI-induced changes predicted lower willingness to adopt AI. Furthermore, individual CanMEDS facets were also tested as predictors for willingness to adopt AI in the “full” linear regression model.

Lastly, post-hoc interaction analyses were performed to explore moderation effects between key predictors (e.g., Skills and Competencies× SDT, SDT × CanMEDS, etc.). Group comparisons (by hospital type, gender, and specialty) were conducted using ANOVA and Kruskal-Wallis tests. Age and Years of work experience were also tested as predictors for willingness to adopt in a multiple linear regression model.

2.4 Integration of Qualitative and Quantitative Phases

For the integration of the Qualitative and Quantitative phases, an integration table was constructed. The integration table consists of five columns. The first contains overarching qualitative themes, while the second lists related sub-themes per row derived from the interview phase. These are accompanied by representative participant quotations from the qualitative interviews in the third column. In the fourth column, corresponding questionnaire items are listed and the final fifth column presents the survey responses from said item related to each theme. Connections between themes and survey items were established through interpretive, manual mapping, informed by the researcher’s understanding of both the qualitative codes and the underlying constructs of the survey. A second researcher reviewed the final table and confirmed the thematic links. While the table itself is not presented as a standalone results section, it served as a tool for guiding interpretation during the discussion phase. As such, the integration matrix acts as a translation device, bridging subjective meaning with measurable patterns and helping to clarify where participant narratives align with, extend, or complicate survey-based insights. The full table can be found in the results section **Table 4.**

3. Results

3.1 Qualitative theme analysis

The coding and thematic analysis of the 20 interviews resulted in five themes emerging with 12 sub-themes. The identified themes include "Preconditions for successful implementation" (*with subthemes: institutional requirements, practical barriers, and relevance to current issues*), "Perceptions on trust and control" (*ethical concerns and technical trust issues*), "Anticipated changes to the profession" (*administrative workload, diagnostic process changes, and patient contact*), "Perspectives on skills and competencies" (*differences across specialisms and anticipated changes in required skills*), and "Motivation explained through SDT" (*competence and autonomy*).

The first theme, being "Preconditions for successful implementation," contains different facets of requirements for the implementation of AI in the medical field according to the participants from the interviews. The sub-theme "institutional requirements" describes requirements that pertain to larger concepts such as legal changes, monetary changes such as costs for the hospital or changes in the educational frameworks of the medical field. The next subtheme, "practical barriers," describes floor level practical issues and requirements for adoption such as not adding extra time loss due to complications with the UI and proper integration into Electronic Health Dossiers. The third sub-theme, "relevance to current issues," highlights the disconnect between the products AI developers design and the desires of the users (in this case the health professionals).

The second theme, being "Perceptions on trust and control," contains two sub-themes. The first sub-theme, "ethical concerns," highlights the worries the specialist's have about who is responsible if a mistake is made and how can privacy properly be kept. The second theme, "technical trust issues," touches on worries about the origin of data and its possible biases, the ability of AI to generate accurate responses without mistakes or hallucinations and the transparency of reasoning from AI models.

The third theme, "Anticipated changes to the profession," contains three sub-themes that are related to expected changes to the profession. The first sub-theme, "administrative workload," highlights the desire and expectation that AI will assist in reducing administrative workload. The second theme, "diagnostic process changes," contains the expectation of changes to the entire diagnostic process. This ranges from changes to the intake conversations or the process for making a diagnosis to changes to the nature of multidisciplinary collaborations to provide healthcare to a patient. The third sub-theme, "patient contact," highlights the expectation that the implementation of AI assistance changes contact with patients, both in time and frequency, with specialists possibly seeing more or less patients for a longer or shorter duration due to information already being preemptively collected, processed and analysed or specialists potentially not having to use their computer to take notes during a consult.

The fourth theme, "Perspectives on skills and competencies," contains two sub-themes that are related to the views of specialists on required skills and competences and possible expected changes to said skills and competences. The first sub-theme, "differences across specialisms," highlights the differences in views on required skills and competences for the different orientations of medical specialism. The second sub-theme,"anticipated changes in required skills," highlights the specialists' expectations on potential changes to their skills and how it might affect competence for medical specialists.

The fifth and last theme is "motivation explained through SDT," which contains the two subscale items of Competence and Autonomy as sub-themes. This main theme touches on the motivation of specialists to adopt AI through the framework of SDT, with the first sub-theme "Competence" highlighting the psychological need of remaining competent when working with or without AI assistance. The second theme, "Autonomy", highlights the psychological need for staying in control of decisions, with the AI never being the shot-caller and again being able to function with or without AI assistance.

3.2 Reliability and Validity Analyses of Quantitative Scales

Skills and Competencies (22 items)

To evaluate internal consistency, both Cronbach's alpha and McDonald's Omega were calculated for the Skills and Competencies (SC) scale. While Cronbach's alpha ($\alpha = 0.73$, 95% CI [0.57, 0.84]) indicated acceptable reliability, it assumes equal item contributions, which may not hold for context-specific or practice-derived scales like this one. Therefore, McDonald's Omega was used as the primary reliability indicator. Omega Total was 0.85, suggesting strong internal consistency without requiring equal item loadings. However, the Omega Hierarchical value of 0.32 and the Explained Common Variance (ECV) of 20% indicated that the Skills and Competencies Scale is likely multidimensional and may reflect multiple underlying constructs.

Item-total correlations ranged from –0.064 to 0.626, with some items (e.g., SC3 and SC20) showing weaker alignment, indicating potential targets for future refinement. To further explore scale structure, an exploratory factor analysis (EFA) using minimum residual extraction and varimax rotation was conducted. Parallel analysis supported a three-factor solution explaining 37% of the total variance. However, the Kaiser-Meyer-Olkin (KMO) value was 0.42, indicating limited sampling adequacy. Bartlett's test was significant ($\chi^2(231) = 367.24$, $p < .001$), but model fit indices pointed to borderline acceptability (RMSR = 0.10; RMSEA = 0.074, 90% CI [0.03, 0.117]). Several items exhibited weak or complex loadings.

SDT (7 items)

For the full SDT scale and the subscales, reliability was again assessed using both alpha and Omega. The full SDT scale demonstrated good internal consistency ($\alpha = 0.86$, 95% CI [0.77, 0.92]). For the subscales, Autonomy showed acceptable reliability ($\alpha = 0.77$, 95% CI [0.60, 0.88]), while Competence was borderline acceptable ($\alpha = 0.69$, 95% CI [0.46, 0.83]). The Relatedness subscale was excluded from internal consistency testing due to it being a single item.

McDonald's Omega Total was 0.93, indicating excellent internal consistency for the combined SDT items. The Omega Hierarchical coefficient (0.70) and ECV (54%) suggested that while subdimensions exist, a general factor likely underlies the scale.

An EFA using minimum residual extraction and varimax rotation confirmed a three-factor structure explaining 72% of the variance. Sampling adequacy was acceptable (KMO = 0.73), and Bartlett's test was significant ($\chi^2(21) = 126.95$, $p < .001$). Model fit indices were strong (RMSR = 0.03; RMSEA = 0.095; TLI = 0.926), although one Ultra-Heywood case (SDT_A3_N) indicated slight model instability. *The full model summaries can be found in appendix tables A1 and A4 to A12.*

3.3 Descriptive statistics Key variables

The descriptive statistics of the numeric key variables can be found in **Table 1**. Participants reported a relatively high willingness to adopt AI, with none of the participants indicating disagreement with the adoption of AI.. The mean Skills and Competencies Total score was also high, as the minimum possible score is 22 and the maximum possible score is 110. The average total score on the Self-Determination Theory (SDT) scale was close to an average of scoring 3 per item, with scores ranging from 13 to 27 across participants. Among the SDT subscales, Competence had the highest average, while Autonomy showed slightly lower scores. Regarding perceptions of how many facets of CanMEDS AI will affect, the average expected amount across CanMEDS domains was close to 3 items selected, with individual scores spanning from 0 to 7.

Table 1

Descriptive Statistics of Numeric Variables

Variable	n	Mean	SD	Min	Max
Willingness to adopt AI	35	4.17	0.71	3	5
Skills and Competencies	35	88.43	6.15	74	99
Autonomy	35	8.80	2.07	4	14
Competence	35	8.94	1.41	6	12
Relatedness	35	2.71	1.02	1	5
SDT Total	35	20.50	3.32	13	27
CanMEDS Expected change Summed	35	2.74	1.80	0	7

As for the individual Perceived and Desired changes to CanMEDS facets, of which the details can be found in **Table 2**, the "Organization" and "Knowledge/ Scientific changes" facets were most often selected as what is Expected and Desired to change.

Table A2

Frequency table of selected variables for Expected and Desired change in the CanMEDS

Variable	Percent Selected %*
Expected change	
Organization changes	71.4
Knowledge / Scientific changes	77.1

Professionalism and Quality changes	22.9
Communication changes	42.9
Collaboration changes	17.1
Social conduct changes	11.4
Professional conduct changes	31.4
Not Applicable	2.9
Other	5.7
Desired change	
Organization changes	62.9
Knowledge / scientific changes	51.4
Social conduct changes	17.1
Professionalism and Quality changes	28.6
Communication changes	31.4
Collaboration changes	17.1
Professional conduct changes	37.1
Not Applicable	2.9
Other	5.7

**note: Percent selected is the % of the population that selected that specific facet, as multiple facets could be selected for this item.*

As for the adoption requirements, which can be found in **Table 3**, “Time and Money” and “Training” were the most frequently selected requirements.

Table 3

Frequency table of selected adoption requirements

Variable	Percent Selected %*
Adoption requirements	
Success stories	34.3
Own successful experience	31.4
Time/money	42.9
Training	60
Other	22.9

**note: Percent selected is the % of the population that selected that specific facet, as multiple facets could be selected for this item.*

3.3 Mixed-Methods Integration table

To connect the thematic insights from the qualitative interviews with the broader descriptive results from the survey, the following **Table 4** integrates qualitative themes with corresponding quantitative data.

Table 4

Integration table of thematic analysis and survey data

Theme	Sub-Theme	Interview quote	Survey question	Survey data
Preconditions for successful implementation	Institutional requirements:	B-02: "Only think that there still are quite a number of privacy issues, legal issues. Cost issues. Maybe even safety issues?" S-06: "Training is needed for this to make people a bit aware that you are still ultimately responsible, You still have to use it, but not. Let it decide for you?"	1. What would be helpful to you for integrating AI in your work environment *(multiple answers possible)* 2. Desired changes in skills and Competencies with the implementation of AI using CANMEDS *(multiple answers possible)*	1. "Training" was selected by 60% of participants as a requirement for adopting AI. Additionally, "Time and/or Money" was selected by 42.9% of participants. "Other" was selected by 22.9% (n = 8) with 6 individuals highlighting time/ money/ different regulations as a requirement. (see **Table 3)** 2. "Organization changes" is the most frequently voted facet with 62.9 % of participants selecting Organization changes as a facet they wish changes. (see **Table 2**)

Preconditions for successful implementation	Practical barriers:	O-05: “It mainly has to stay practical and fast, because we have too little staff and we have a lot of patients, so we have really converted that into a practical working method.” S-08: “And step 3 is that you must have a good integration with your current EHR.” O-01: “And yes if I suppose, I want to look at a lung photo. I already need 10 algorithms to look at it."	1. What would be helpful to you for integrating AI in your work environment *(multiple answers possible)* 2. Desired changes in skills and Competencies with the implementation of AI using CANMEDS *(multiple answers possible)*	1. Of the 22.9% of "other" selected as a requirement for implementation, only one person highlighted needing proper integration into the current workflow as a requirement for implementation. (see **Table 3)** 2. "Knowledge / scientific changes" is the second most frequently voted facet with 51.4% of participants selecting this as a facet they wish changes with the implementation of AI. (see **Table 2**)
Preconditions for successful implementation	Relevance to current issues:	B-01: “The most important thing is that things align, So that an AI tool solves something, sort of not that it is presented as like "this is how you should work" and then afterwards it leads nowhere”	1. What would be helpful to you for integrating AI in your work environment *(multiple answers possible)*	1. The same individual that highlighted proper integration also highlighted that "the AI needs to actually solve a relevant issue".(see **Table 3)** Furthermore, "Organizational changes" was selected in wishes for change in the CANMEDS facets by 71.4% of participants. (see **Table 2**)
Perceptions on trust and control	Ethical concerns:	B-03: “but then with an AI system that stays within 4 walls. So where you don’t like with copilot or ChatGPT, yeah or copilot maybe then yes. But or the deapseek Chinese variant where you don’t know where your data stays?” S-02: “Another aspect of ethics could be that you say like okay, I use it for example for a decision that I make as a doctor. And that decision turns out not to be good. Yes to what extent is then AI responsible for example? Or, are you still responsible?"	1. What would be helpful to you for integrating AI in your work environment: *(multiple answers possible)* 2. *(How much do you agree with this statement):* SC17: Skills and Competencies of a medical professional means Taking responsibility in complex situations and acting based on insight and experience. 3. *(How much do you agree*	1. Only one open answer which follows" "transparency and explainability, say, ownership, control" highlighted this requirement. 2. With a mean of 4.4 (SD = 0.65), 48.6% selected strongly agree, 42.9 selected slightly agree and 8.6% selected neutral. 3. With a mean of 4.46 (SD = 0.51) 45.7% selected strongly agree, 54.3% selected slightly agree

			with this statement): SC22: Skills and Competencies of a medical professional means Making responsible decisions in situations of medical uncertainty.	
Perceptions on trust and control	Technical trust issues:	O-03: “where the data come from that you have to be transparent about that and ethical about that and that it has to be inclusive enough.” S-08: “If I want to know something about a certain syndrome or a condition that I have too little knowledge about and I get a nice summary. I think like, is this actually correct? Or I want to know a bit more about that. Then I do want that device to also be able to give me a source citation. or something like that. That is actually correct, so a big part transparency is important..” B-02: “Why I also say that that that transparency is so important is that you do have to know what is happening and that you also have to be able to look it up and be able to see like how does it actually get there and that you definitely should not blindly rely on it?"	*(not available, see limitations)*	*(not available, see limitations)*

Anticipated changes to the profession	Administrative workload	S-03: “Well it would Naturally be brilliant If you just have the conversation with a patient and that you don’t have to write anything down and that it just automatically goes into the file.” B-06: “for example summarizing a conversation eventually for in the file. Those kinds of applications relatively simple applications if you ask me but.Which could be very useful.” S-05: “That administrative burden. That would really be a huge gain if something. If there if that could be improved, sort of.” S-09:” I want: less behind that computer more in front of my patient"	1. What would be helpful to you for integrating AI in your work environment *(multiple answers possible)*	1. Of the 22.9% that selected "other", 3 open answers highlighted aid in administrative workload. (see **Table 3**)
Anticipated changes to the profession	Diagnostic process changes	O-02: “so at the moment that you do a bit of diagnostics for example, then you will soon have a conclusion from the AI and a bit of conclusion, Maybe from the doctor and those two will only come together later and then but also in a way that it is verifiable.” S-03: “And, I also think supportive in. Transferring knowledge, and then you naturally get ideas, options about what kind of treatment and then you can with your own knowledge that what you what you get sent, that you can make a choice with that and what then is the best?"	1. Expected changes in skills and Competencies related to the diagnostic process using CANMEDS *(multiple answers possible)*	1. 77.1% of participants selected "Knowledge/Scientific changes" as a CanMEDS facet they expect to change, 42.9% selected "Communication changes," and 31.4% selected "Professional conduct changes." (see **Table 2**)

Anticipated changes to the profession	Patient contact	B-01: "Maybe you should already run people through a certain kind of scan beforehand, before they even sit in your consultation room. And then you can already separate the wheat from the chaff." O-04: "If it goes a bit easier, so hopefully even more People. Actually be able to offer the optimal care. Now it is often also still the case that with some patients you think like well, is there really added value to do this completely? And that can then be deployed at a slightly lower threshold so, because of that you can eventually also offer this to more patients."	1. Expected changes in skills and Competencies related to patient contact using CANMEDS *(multiple answers possible)* 2. *(How much do you agree with this statement):* The use of AI will help me to feel more connected to my patients or colleagues.	1. 42.9% of participants selected "Communication changes" as a CanMEDS facet they expect to change, 22.9% selected "Professionalism and Quality changes," and 11.4% selected "Social conduct changes." (see **Table 2**) 2. With a mean of 2.71 (SD = 1.02), which leans toward slightly disagree (2), 11.4% selected strongly disagree (1), 31.4% selected slightly agree (2), 34.3% selected neutral (3), 20% slightly agree (4) and 2.9% strongly agree (5)
Perspectives on skills and Competencies	Differences across Specialisms	B-04: "Then you have the CanMed model that has very different Competencies and for example, look at such a meeting that we had yesterday within my department and then you see all kinds of different types." B-05 : "An internist would put diagnostics higher, while with us it is a bit lower. (In the context of the ranking assignment)"	1. ranking of 10 skills and Competencies for medical specialists	*For the supportive group (O*), the top three ranked skills and Competencies were complex problem solving (M = 2.33, SD = 2.31), sharing knowledge and supporting colleagues (M = 2.33, SD = 1.53), and acting with an eye for the sustainability and effectiveness of care (M = 3.33, SD = 1.53). *In the cognitive group (B*), empathic communication ranked highest (M = 2.64, SD = 2.01), followed by putting patients and loved ones first (M = 2.82, SD = 2.44), and complex problem solving (M = 4.91, SD = 3.14). *The intervention group (S)* prioritized putting patients and loved ones first (M = 2.44, SD = 2.06), followed by empathic communication (M = 3.81, SD = 2.37), and complex problem solving (M = 4.12, SD = 3.03). *(These values represent the mean rank scores (M) and standard deviations (SD) of Skill/Competence rankings when combining individual rankings to create group*

				rankings, this means that the highest average ranked skill/competence is the rank 1 for that group, the second highest average ranked is rank 2 etc, SD’s were reported for more detail.). ***See table A21 in the appendix for the full rankings.***
Perspectives on skills and Competencies	Changes in required Skills and Competences	B-01: “Well, it might maybe take over part of the diagnostic skills. What is the effect on the doctor? Yes, that you in that sense that you then. Can be supported in that. I do think that the next generation of doctors who then have not learned to reason themselves, learn that they also can no longer do without it.” O-02: “Well, let me put it this way, a doctor who does not stick to number 6 and 5 at this moment, right? So the continuous further development of knowledge and reflective skills, is going to suffer from losing this knowledge and skills. The doctors who do go along with this, are only going to become stronger from it."	1. Expected changes in required skills and Competencies using CANMEDS *(multiple answers possible)* 2. *(How much do you agree with this statement):* AI has a negative effect on my judgment.	1. 77.1% of participants selected "Knowledge/Scientific changes" as a CanMEDS facet they expect to change, 42.9% selected "Communication changes," and 31.4% selected "Professional Conduct changes." (see **Table 2**) 2. With a mean of 2.2 (SD = 0.83), 20% selected strongly disagree (1), 45.7% selected slightly disagree (2), 28.6% selected neutral (3) and 5.7% selected slightly agree (4)
Motivation explained through competence and autonomy (SDT)	Competence	O-01: “And to continue weighing that and not blindly start trusting the algorithm, becauseiIt is naturally wonderful and great if you are being helped and you are presented with a a result and you can always adopt it. So the staying critical of the results. I think that that is going to become very important. And being able to interpret the results and and to explain them to your colleagues.” S-05: “I would find it very nice if medical or paramedical professionals with those guidelines at least have a basic. Knowledge of the a model that they will use in practice, so that they at least if they would look it up can to a certain extent understand it."	*(How much do you agree with this statement):* 1. I feel confident in my ability to use AI effectively in my clinical work. 2. The use of AI will help me to feel more skilled and competent as a medical professional. 3. AI has a negative effect on my judgment.	1. With a mean of 3.51 (SD = 0.98), 17.1% selected slightly disagree (2), 31.4% selected neutral (3), 34.3% selected slightly agree (4) and 17.1% selected strongly agree (5) 2. With a mean of 3.23 (SD = 0.88), 22.9% selected slightly disagree (2), 37.1% selected neutral (3), 34.3% selected slightly agree (4) and 5.7% selected strongly agree (5) 3. With a mean of 2.2 (SD = 0.83), 20% selected strongly disagree (1), 45.7% selected slightly disagree (2), 28.6% selected neutral (3) and 5.7% selected slightly

				agree (4)
Motivation explained through competence and autonomy (SDT)	Autonomy	S-09: "I think that the "Human in the loop" in healthcare in general is desired." O-03: "So you really have to invest in the human and you must therefore also. You must also be able to make do without it, But I think that is not going to work. But that is my ethical conviction that you as a human should also be able to function without AI."	*(How much do you agree with this statement):* 1. I feel that I can decide for myself how I use AI in a way that fits my clinical judgment. 2. I have the freedom to decide if and how AI supports my work. 3. I am afraid that AI undermines my autonomy as a doctor.	1. With a mean of 3.23 (SD = 1.14), 8.6% selected strongly disagree (1), 17.1% selected slightly disagree (2), 28.6% selected neutral (3), 34.3% selected slightly agree (4) and 11.4% selected strongly agree (5) 2. With a mean of 3.2 (SD = 1.23), 11.4% selected strongly disagree (1), 20% selected slightly disagree (2), 17.1% selected neutral (3), 40% selected slightly agree (4) and 11.4% selected strongly agree (5) 3. With a mean of 3.63 (SD = 1), 2.9% selected strongly disagree (1), 11.4% selected slightly disagree (2), 22.9% selected neutral (3), 45.7% selected slightly agree (4) and 17.1% selected strongly agree (5)

3.4 Willingness to adopt AI predicted by independent variables

Two Multiple Linear regression models were constructed to predict Willingness to adopt AI, a "Full" model with all the subscale scores as predictor and the Skills and Competences total score and a "Simple" model with the summed scores for predictors that were split up in smaller variables in the "Full" model.

Full model

The full model multiple linear regression analysis was conducted to examine whether the view on Skills and Competencies, satisfaction of psychological needs (Autonomy and Competence and Relatedness), and expectations of change in the CanMEDS Facets predicted willingness to adopt AI. After StepWise variable selection, 5 of the 7 CanMEDS facets and Relatedness from SDT were removed. The final "full" model was statistically significant, $F(5, 29) = 7.53$, $p = .0001$, explaining 56.5% of the variance in willingness to adopt AI (Adjusted $R^2 = .490$). Among the predictors, Skills and Competencies Total score was a strong positive predictor ($\beta = 0.049$, $p = .002$). Competence, representing the psychological need for feeling capable, also significantly predicted willingness to adopt AI ($\beta = 0.181$, $p = .013$). In contrast, Expected Knowledge/ Scientific changes, negatively predicted willingness to adopt AI ($\beta = -0.622$, $p = .009$). Autonomy and Expected Professional Conduct changes did not reach statistical significance (ps > .15). A detailed summary of the regression coefficients is presented in **Table 5.**

Table 5

Full Multiple Linear Regression model with Willingness to adopt as a dependent variable

term	estimate	std.error	statistic	p.value
(Intercept)	-0.83	1.34	-0.62	0.54
Skills and Competencies	0.05	0.01	3.4	0.002*
Autonomy	-0.06	0.04	-1.45	0.16
Competence	0.18	0.07	2.66	0.013*
Expected Knowledge/ Scientific changes	-0.62	0.22	-2.79	0.0092*
Expected Professional Conduct changes	0.28	0.19	1.46	0.16

**Note: $p < 0.05$*

Assumptions of linear regression were checked and met. Residual plots indicated approximate linearity and homoscedasticity, and Q-Q plots suggested normality of residuals, supported by a non-significant Shapiro-Wilk test ($W = 0.97$, $p = .459$). Variance Inflation Factors (VIFs) ranged from 1.05 to 1.24, indicating no problematic multicollinearity. Detailed diagnostic plots and VIF values can be found in **Appendix Figure A4** and **Table A22**.

Simple model

The simple multiple linear regression analysis was conducted to examine whether the SDT total score, Skills and Competencies total score and the summed amount of selected CanMEDS facets predicted willingness to adopt AI. After StepWise variable selection, the summed amount of selected expected CanMEDS changes was removed. The overall model was statistically significant, $F(2, 32) = 4.90$, $p = .014$, and explained 23.4% of the variance in willingness to adopt AI ($R^2 = .234$, Adjusted $R^2 = .187$). Among the predictors, the Skills and Competencies total score was a significant positive predictor ($\beta = 0.045$, $p = .018$). The SDT total score was not a significant predictor ($\beta = 0.053$, $p = .119$). A detailed summary of the regression coefficients is presented in **Table 6**.

Table 6

"Simple" StepWise Regression model with Willingness to adopt as dependent variable

term	estimate	std.error	statistic	p.value
(Intercept)	-0.86	1.65	-0.52	0.61
SDT full scale	0.05	0.03	1.6	0.12
Skills and Competencies	0.04	0.02	2.5	0.02*

**Note: $p < 0.05$*

Assumption checks for the simplified regression model indicated no substantial violations. Residuals appeared linear, approximately normally distributed (Shapiro-Wilk $W = 0.97$, $p = .459$), and homoscedastic. VIFs were well within acceptable limits (1.01), confirming absence of multicollinearity. Further diagnostic information is available in **Appendix Figure A5** and **Table A22**.

Hypothesis testing:

Hypothesis 1, which stated that "Greater satisfaction of psychological needs *(autonomy, competence, and relatedness)* is positively associated with intention to adopt AI in clinical practice", was tested with the Simple multiple linear regression model. The <u>*SDT total score*</u> (all seven items summed) did not predict willingness to adopt AI ($\beta = .25$, 95% CI [–0.01, 0.12], $p = .119$, partial $\eta^2 = .10$). Therefore, Hypothesis 1 is not supported.

Hypothesis 2, which stated that "Stronger beliefs about core skills and competencies for medical professionals *(Skills and Competencies Total score)* are associated with greater willingness to adopt AI," was tested with both the "full" and "simple" multiple linear regression model. Supporting Hypothesis 2, Skills and Competencies total score significantly predicted willingness to adopt AI with the *Simple model* ($\beta = .39$, 95 % CI [0.01, 0.08], $p = .018$), medium effect ($\eta^2 = .16$, $\omega^2 = .13$) and the *Full model:* ($\beta = .43$, 95 % CI [0.02, 0.08], $p = .002$), medium-to-large effect ($\eta^2 = .28$, $\omega^2 = .23$).

Lastly, hypothesis 3, which stated that "Medical professionals who expect AI to alter a larger amount of core facets of medical Skills and Competencies (CanMEDS Facets) are less willing to adopt AI," was not supported in its original form, with the total number of expected CanMEDS changes being removed from the simple model with StepWise variable selection and therefore did not significantly predict willingness to adopt AI. However, after StepWise variable selection for the "full" model with individual CanMEDS domains, the Knowledge and Scientific facet did significantly predict willingness to adopt AI (β = –.38, 95% CI [–1.08, –0.17], p = .009, partial η^2 = .21, partial ω^2 = .16). Expected changes in the Professional Conduct domain were non-significant (β = .18, 95% CI [–0.11, 0.66], p = .156).

Additional analyses done for saxion:

Demographic predictors, including age, gender, work experience, and hospital type, were not significantly associated with willingness to adopt AI. A trend toward group differences across specialism types approached significance (Kruskal-Wallis $\chi^2(5)$ = 9.57, p = .088). Due to the limited sample size, exploratory interaction models lacked sufficient power and were therefore not included in the final analysis. *Full model summaries remain available in Appendix A13–A20 for reference.*

4. Discussion

4.1 Answering the Research Questions

The first research question explored the perceived influence medical specialists have of AI on the needed skills and competences for their medical profession. Interviewees portrayed AI as a potentially helpful colleague, one that pre-screens images, drafts notes, supports in diagnostic decisions and therefore frees up time for patient contact. This aligns with previous literature highlighting AI’s capability to reduce administrative and cognitive burdens, thereby allowing medical professionals to focus on more critical and patient-centered tasks (Huo et al., 2025; Alowais et al., 2023). When looking at **Table 4**, quotes that touch one the potential for administrative support or decision support are accompanied with open answers touching on a reduction of administrative load from adoption requirements and wishes for changes in Organization which encompasses the ability of Medical Specialists to plan, coordinate and manage healthcare processes, which includes administrative load and schedules for work hours. This finding corroborates existing studies suggesting AI implementation can significantly enhance administrative efficiency and workflow management (Jiang et al., 2017). However, perceptions of AI's impact on skills and competencies became less positive when AI was seen as reducing professional autonomy or undermining competence by encouraging reduced critical thinking or over-reliance, potentially leading to skill degradation over time. Literature consistently supports these concerns, emphasizing that over-reliance on AI may cause deskilling, diminished clinical judgment, and decreased professional autonomy (Goh et al., 2024; Agarwal et al., 2024; Alowais et al., 2023). Hence, respondents insist on options for human overruling and AI training before AI adoption. Therefore, the influence of AI on Skills and Competences is a double sided edge, it can both enhance and diminish the Skills and Competences based on the context of implementation and the specific type of AI.

The second research question explored the effects of how the perceptions of medical skills and competencies, the expectations of changes on those skills and competencies with the implementation of AI and the satisfaction of basic psychological needs influence the medical specialist’s willingness to adopt AI through three hypotheses. These hypotheses were tested in the quantitative side of this report, however, given that the scales were custom-developed and the analysis was exploratory with the regression models having limited power, all models should be interpreted with caution. The first hypothesis, which stated that “Greater satisfaction of psychological needs *(autonomy, competence, and relatedness)* is positively associated with intention to adopt AI in clinical practice,” and the third hypothesis, which stated that “Medical professionals who expect AI to alter a larger amount of core facets of medical Skills and Competencies (CanMEDS Facets) are less willing to adopt AI,” were both not supported. However, the second hypothesis, which stated that “Stronger beliefs about core skills and competencies for medical professionals *(Skills and Competencies Total score)* are associated with greater willingness to adopt AI,” was supported. In practical terms, a specialist's willingness to adopt AI was shaped by multiple factors, but in hypothesis testing and thus in answering the second research question only one variable significantly predicted willingness to adopt AI. The more strongly they view skills and competencies, the more willing they are to adopt AI. Furthermore, even though the total SDT score was not a significant predictor, when specialists felt personally competent in using AI, their willingness to adopt AI increased significantly. This was measured in the Competence subscale of the custom scale based on Self Determination Theory (Ryan & Deci, 2018) developed specifically for this study to explore the workings of motivation for adopting AI and supports literature that emphasizes the role of perceived competence in adopting new technologies (Ryan & Deci, 2018; Bergdahl et al., 2023). Lastly, the overall CanMEDS score, which sums up all professional competency areas they expect to change with the adoption of AI, showed no clear influence on whether the willingness to adopt AI. However, the individual CanMEDS change of Knowledge/Science did significantly predict negative willingness to adopt AI, which together with the qualitative interview themes highlights that specialists are more cautious about adopting AI when it might adjust core facets of medical specialism such as knowledge. This is consistent with literature emphasizing that while AI can aid knowledge dissemination, excessive reliance may threaten core medical knowledge and decision-making capacities (Goh et al., 2024; Huo et al., 2025). Furthermore, identity-oriented work from East-Asian tertiary hospitals shows that practitioners who define themselves by a broad, patient-centred competence profile are more inclined to experiment with supportive technologies (Yu et al., 2025). That pattern helps explain why respondents who saw AI as expanding, rather than displacing, their repertoire expressed greater openness. It also resonates with Self-Determination Theory research, which finds that competence needs spur exploration only when users feel their expertise is still recognised (Bergdahl et al., 2023). Collectively, the findings in this study together with literature suggests that "Capability Assurance", the requirement that AI will support rather than erode specialist's ability to practise safely and capably even when systems crash, the AI fails or any other circumstance that requires the Specialist to act autonomously and competently, could be a missing piece in AI adoption frameworks. Incorporating this facet may resolve the apparent paradox between specialist's desire for training and their resistance to knowledge and scientific related changes.

When integrating the findings from this study with the literature to assess theoretical implications, Self-Determination Theory was adjusted as a base framework for technology uptake in terms of how well new tools satisfy autonomy, competence and relatedness needs (Ryan & Deci, 2018). The present study supports the idea of autonomy, relevant mostly in the qualitative findings, and competence, being a significant predictor for willingness to adopt AI, being relevant in the adoption of AI by combining them into "Capability-Assurance". When specialists sensed that AI would extend their skills while leaving final judgment in human hands, the technology felt competence-enhancing. When it seemed to replace core diagnostic reasoning, or to leave them helpless in the event of failure, it felt competence-eroding. In short, capability assurance appears to highlight whether the competence and autonomy needs are satisfied or thwarted. This insight helps knit together two lines of research that have often been treated separately. Identity-oriented studies show that specialists with a broad, patient-centred skill outlook are more receptive to supportive technologies (Yu et al., 2025). Trust models, in turn, highlight transparency and clear error accountability as gateways to adoption (Wang & Wang, 2024; Ratta et al., 2025). Both strands converge when viewed through the lens of capability assurance, where tools that let specialists maintain (and if necessary reclaim) their own expertise simultaneously reinforce feelings of competence and nurture trust, whereas tools that obscure their reasoning or leave them unable to intervene erode both. The CanMEDS "professional conduct" facet translated from Dutch acts as the hub that integrates all others (Frank et al., 2015). When AI appears to weaken that central link, by sidelining human decision-making authority, resistance naturally rises, echoing Ten Cate's (2005) warning that learning environments must keep practitioners in legitimate, hands-on roles. However, this was not reflected in the current quantitative analysis, even though the StepWise Variable Selection did not remove the Autonomy and CanMEDS professional conduct variables from the regression models so a possible larger sample size might provide different results. Nevertheless, adoption models in healthcare could therefore move beyond generic "perceived usefulness" constructs and explicitly incorporate capability assurance as a prerequisite for adoption. Finally, the tension specialists expressed between welcoming training and resisting knowledge displacement refines SDT's competence pathway, where motivation surges when AI is framed as expanding specialist's capabilities while preserving their final judgment, but fades when it hints at replacement.

To translate these insights into day-to-day implementation, hospital leaders could begin by framing AI as a "competence amplifier", not a replacement. Describing new tools as a "second set of eyes" that sharpens clinical reasoning and lightens paperwork signals that a specialist's authority, and thus their capability assurance, remains central. Which is a message that directly fulfils the competence and autonomy needs emphasised by Self-Determination Theory (Ryan & Deci, 2018). That framing must be backed by transparent interfaces and reliable override options: dashboards that reveal decision paths, uncertainty bands and error logs that let specialists audit the algorithm and step in when necessary. Furthermore, with lack of time being the most common practical barrier, adoption efforts could rely on task-specific micro-training, utilising five-minute e-modules slotted into existing Medical Education platforms, which allow doctors to practise new workflows without feeling that the profession itself is being re-tooled (Bergdahl et al., 2023). Roll-outs can then be phased from peripheral to core knowledge tasks, starting with AI that automates routine documentation or scheduling, and only later add decision support that touches diagnostic reasoning. This staged approach honours Ten Cate's (2005) principle of "legitimate peripheral participation," letting specialists build confidence before the system approaches the centre of their expertise. Finally, co-designed governance structures, clear protocols for error handling, data stewardship and medicolegal liability are essential. Such agreements make lines of accountability explicit, satisfy relatedness by involving specialists in rule-setting, and preserve capability assurance by ensuring that human judgement remains the recognised back-stop if the AI or infrastructure fails. Together, these linked actions turn abstract concerns about capability loss into concrete design choices, giving specialists the practical confidence they need to welcome AI as a trustworthy ally.

4.2 Limitations and Strengths

This study offers several methodological and conceptual strengths. First, the use of methodological triangulation, combining in-depth exploratory interviews with a follow-up survey, supplied both narrative richness and broader confirmation, showing that the ambivalence voiced by individual specialists also appears at cohort level. Second, framework alignment with both the CanMEDS competency model (Frank et al., 2015) and Self Determination Theory (Ryan & Deci, 2018) provided a coherent lens for linking professional identity, motivational processes and technology attitudes. Third, the work enjoys strong ecological validity because all participants were practising specialists who engaged with realistic task scenarios, ensuring that the insights speak directly to day-to-day implementation planning.

However, several limitations moderate the study's generalisability. Survey completion was limited, with fewer than half of the specialists who opened the questionnaire submitting usable data. Most drop outs likely reflected time constraints with specialists already having little to no time to finish their tasks related to patient care. Next to the high drop-out rate, the sample is fully Dutch and therefore generalization beyond the context of the Dutch healthcare system is not possible. Furthermore, measurement precision also warrants caution, because the Skills-and-Competencies list showed multiple underlying dimensions and a few weak items, suggesting that further scale development, paired with larger and possibly different samples are needed to confirm its structure.. Next to this, the abbreviated custom SDT scale hampers comparison with established metrics because psychometric soundness could not be established with the small sample size for a stable factor analysis or reliable Cronbach's alpha. Lastly, the interactive CanMEDS item captures only the breadth of expected impact, as in how many facets respondents clicked, without recording either the depth of influence within each facet or whether that influence is perceived as beneficial or disruptive. Therefore, a respondent who expects a large effect on a single facet is indistinguishable from one who expects small effects across three facets, which limits interpretability. In addition, a timing mismatch arose because the qualitative coding was still under way when the survey was in construction, leaving a handful of questionnaire items only loosely tied to later-emerging themes. Although theme definitions were refined through peer debriefing, no formal inter-rater statistic was calculated, so qualitative reliability remains an open question. Finally, construct clarity suffered occasionally as the project bridged both language differences between Dutch and English and between human-resource terminology and psychological theory. A difference can for example be found in the Canadian version of the CanMEDS figure and the Dutch version, with the Canadian version using “roles” but the Dutch version using facets. Next to this, Saxion was looking into “craftsmanship,” which is a human resources term that is not used in psychology and therefore had to be translated to “skills and competences” for proper analysis. Taken together, these constraints limit how far the findings can be generalised beyond the present sample, yet they do not undermine the study’s central contribution which attempted to demonstrate how capability assurance, the belief that AI will support rather than erode specialist’s ability to practise safely and competently, shapes professionals’ motivational response to intelligent systems.

4.3 Future research

Looking ahead, three research avenues deserve additional attention. First, the desire for training still deserves closer study, not because it is inherently paradoxical, but because its motivational impact depends on how AI is presented. Controlled experiments that frame the technology either as a skill-extender or as a potential substitute could pinpoint the moment at which learning opportunities stop feeling empowering and start feeling threatening, thereby sharpening the use of Self-Determination Theory (Ryan & Deci, 2018) as a framework for specifically AI adoption. Second, the Skills and Competencies scale was constructed due to no existing Dutch instrument capturing the construct this study required. Generic professionalism scales such as the 22-item Professionalism Assessment Scale (PAS) (Klemenc-Ketiš & Vrečko, 2014) and the 36-item Penn State College of Medicine Professionalism Questionnaire (Blackall et al., 2007) assess broad values like empathy, responsibility and integrity, but they omit domain-specific competencies (e.g., protocol-free decision-making, diagnostic focus under time-pressure). Adapting those scales would therefore have required extensive re-wording and item addition, so a new 22-item Dutch Skills and Competencies scale based on the qualitative insights and tailored to practising specialists was developed and its face/content was validated. Therefore, the Skills and Competencies scale should be subjected to full psychometric vetting. A multi-centre validation, pairing Delphi consensus work in a focus group with Medical Specialists together with item-response modelling, could confirm its factor structure, eliminate weak statements and generate specialty-specific norms, which could provide a reliable tool for tracking how distinct competencies shape AI attitudes. Lastly, researchers could look into charting the boundaries between AI-assisted and exclusively human tasks. Scenario surveys and workflow simulations in which specialists classify activities such as triage, imaging annotation or medication titration would reveal where they draw the line between augmentation and delegation, providing concrete guidance for scope-of-practice policies and interface design. Pursuing these three lines of inquiry could fill the conceptual gaps highlighted in this study and move the field toward safer, more specialist-centred deployments of Artificial Intelligence.

5. Conclusion

This mixed-methods study, which combined in-depth interviews with a follow-up survey built from those narratives, linked specialist’s lived experiences of artificial intelligence directly to statistically tested adoption drivers. Drawing on a sample of practising Dutch specialists, the design explored qualitative themes that were generalised and examined. Both strands of evidence converged on the same message. Interviewees welcomed AI as a “second set of eyes” that speeds up diagnosis and clears paperwork, yet they grew wary whenever the technology seemed to displace the autonomic and competent core of medical expertise. In other words, this research suggests that a decisive factor is “capability assurance”, where specialists are eager to use AI when it clearly amplifies their expertise and keeps them in control, but hesitate when it threatens to overwrite or obscure it. These findings extend adoption models by suggesting that enthusiasm for AI depends less on generic tech optimism and more on a nuanced belief that the technology will not harm, but strengthen professional competence. Implementation efforts that frame AI as a skill enhancer, provide transparent AI with traceable decision documentations and guarantee reliable human override are therefore best placed to turn AI into a trusted clinical ally rather than a disruptive rival.

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7. Appendix

Appendix A: Figures and tables

Figure A1
Exact version of Dutch CanMEDS used in Questionnaire

Table A1
Cronbach's Alpha of Full SDT scale

raw_alpha	std.alpha	G6(smc)	average_r	S/N	ase	mean	sd	median_r
0.85	0.86	0.9	0.47	6.14	0.038	3.33	0.75	0.49

Table A2

Frequency table of selected variables for Expected and Desired change in the CanMEDS

Variable	Percent Selected %
Expected change	
Organization changes	71.4
Knowledge / scientific changes	77.1
Professionalism and Quality changes	22.9
Communication changes	42.9
Collaboration changes	17.1
Social conduct changes	11.4
Professional conduct changes	31.4
Not Applicable	2.9
Other	5.7
Desired change	
Organization changes	62.9
Knowledge / scientific changes	51.4
Social conduct changes	17.1
Professionalism and Quality changes	28.6
Communication changes	31.4
Collaboration changes	17.1
Professional conduct changes	37.1
Not Applicable	2.9
Other	5.7

Table A3

Frequency table of selected adoption requirements

Variable	Percent Selected %
Adoption requirements	
Success stories	34.3
Own successful experience	31.4
Time/money	42.9
Training	60
Other	22.9

Table A4

Autonomy cronbach's alpha

Raw.Alpha	Standardized.Alpha	Average.Inter.Item.Correlation	Sample.Size
0.77	0.77	0.52	35

Table A5

Competence cronbach's alpha

Raw.Alpha	Standardized.Alpha	Average.Inter.Item.Correlation	Sample.Size
0.69	0.69	0.43	35

Table A6

Skills and Competenciescronbach's alpha

Raw.Alpha	Standardized.Alpha	Average.Inter.Item.Correlation	Number.of.Items	Sample.Size
0.73	0.79	0.14	22	35

Table A7

Skills and CompetenciesEFA loadings

Item	MR1	MR3	MR2
SC1	0.41	0.44	-0.34
SC2	0.23	-0.13	0.54
SC3	-0.058	0.12	0.096
SC4	0.05	0.56	-0.25
SC5	0.53	0.12	0.10
SC6	0.73	0.15	0.23
SC7	0.39	0.39	0.14
SC8	0.33	0.054	0.029
SC9	0.23	0.052	0.81
SC10	0.11	0.58	-0.024
SC11	0.25	0.48	-0.048
SC12	0.33	0.23	0.45
SC13	0.76	0.11	-0.066
SC14	0.45	0.18	0.059
SC15	0.13	0.41	-0.018
SC16	0.52	-0.40	-0.077
SC17	0.0048	0.69	0.27
SC18	0.52	0.32	0.016
SC19	0.03	-0.068	0.57
SC20	0.37	-0.16	-0.66
SC21	0.11	0.5	-0.006
SC22	0.26	0.47	0.18

Table A8

Skills and CompetenciesKMO and Bartlett

KMO.Overall	Bartlett.Chi.Square	Bartlett.df	Bartlett.p.value
0.42	367.24	231	2.84E-08

Table A9

Skills and CompetenciesMcdonald’s Omega

Omega.Total	Omega.Hierarchical	Explained.Common.Variance..ECV.
0.85	0.32	0.199

Figure A2

Skills and CompetenciesMcDonald’s Omega

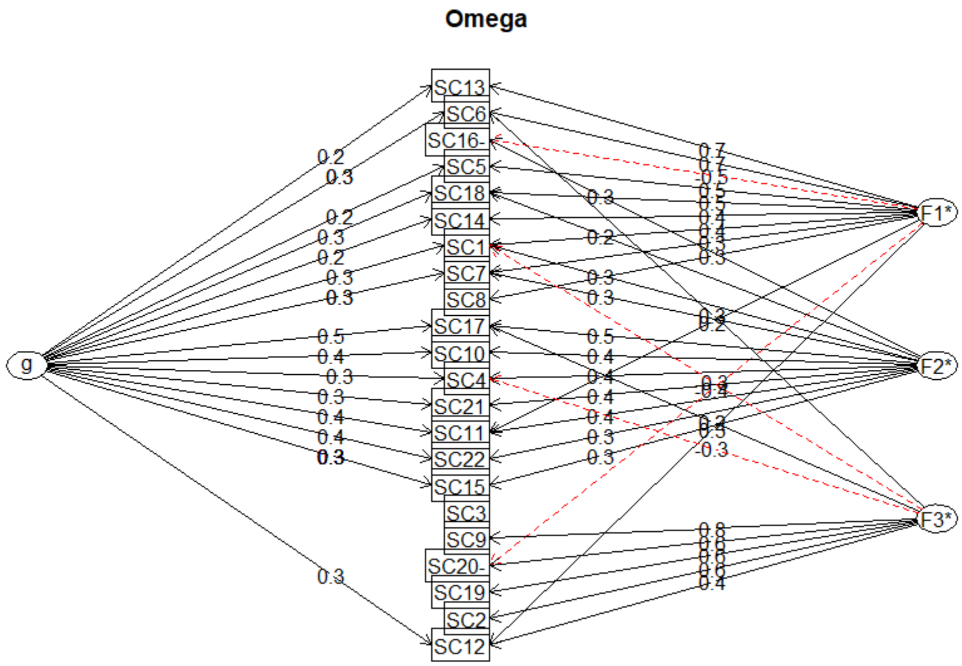

Table A10

SDT EFA loadings

	MR1	MR3	MR2
SDT_A1	0.38	-0.26	8.89E-01
SDT_A2	0.11	-0.12	0.82
SDT_A3_N	-0.27	0.96	-0.16
SDT_C1	0.47	-0.40	0.14
SDT_C2	0.65	-0.35	0.22
SDT_C3_N	-0.29	0.59	-0.18
SDT_R1	0.89	-0.23	0.22

Table A11

SDT KMO Bartlett

KMO.Overall	Bartlett.Chi.Square	Bartlett.df	Bartlett.p.value
0.73	126.95	21	3.73E-17

Table A12

SDT McDonald's Omega

Omega.Total	Omega.Hierarchical	Explained.Common.Variance..ECV.
0.93	0.7	0.542

Figure A3

SDT McDonald's Omega

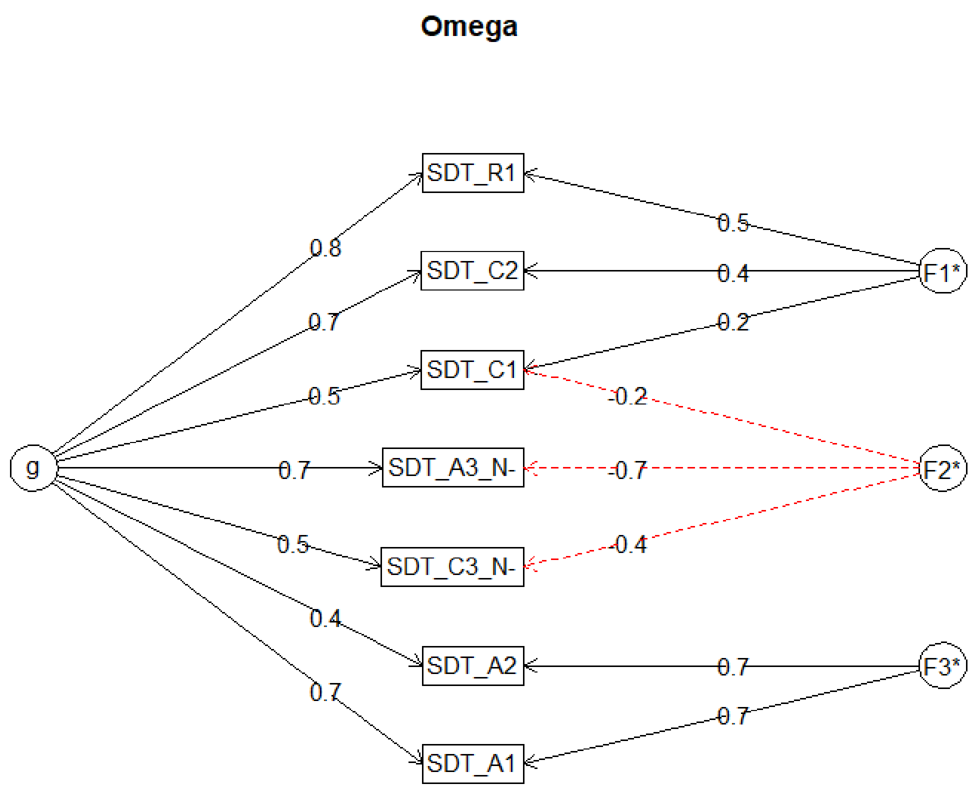

Table A13.1

Multiple linear model of Willingness to adopt AI over Age and Work experience

term	estimate	std.error	statistic	p.value
(Intercept)	3.9	0.64	6.07E+00	8.95E-07
Age	0.0072	0.024	0.3	0.77
Work experience	-0.017	0.18	-0.098	0.92

Table A13.2

Stats of multiple linear model A13.1

r.squared	adj.r.squared	sigma	statistic	p.value	df	logLik	AIC	BIC	deviance	df.residual	nobs
0.0068	-0.055	0.73	1.09E-01	8.97E-01	2	-36.88	81.75	87.98	16.86	32	35

Table A14

Group comparisons for predicting

Group	Test	Statistic	p_value	Significant
Gender	ANOVA	$F(1, 33) = 1.571$	2.19E-01	No
Type of Hospital	Kruskal-Wallis	$\chi^2(2) = 1.74$	0.418	No
Specialism Group	Kruskal-Wallis	$\chi^2(5) = 9.57$	0.088	No (trend)

Table A15

Interaction effect SDT: Autonomy (centered) x CanMEDS: Knowledge/ Scientific changes (centered) on Willingness to adopt

term	estimate	std.error	statistic	p.value
(Intercept)	4.17	0.11	3.75E+01	2.16E-27
Autonomy (centered)	-0.02	0.055	-0.37	0.72
CanMEDS Knowledge/ Scientific expected (centered)	-0.74	0.27	-2.79	0.009
Autonomy (centered) : CanMEDS Knowledge/ Scientific expected (centered)	0.05	0.13	0.37	0.71

Table A16
Interaction effect SDT: Competence (centered) x CanMEDS: Knowledge/ Scientific (centered) changes on Willingness to adopt

term	estimate	std.error	statistic	p.value
(Intercept)	4.23	0.11	3.96E+01	4.08E-28
Competence (centered)	0.19	0.076	2.46	0.02
CanMEDS Knowledge/ Scientific expected (centered)	-0.70	0.29	-2.45	0.02
Competence (centered) : CanMEDS Knowledge/ Scientific expected (centered)	0.27	0.2	1.4	0.17

Table A17
Interaction effect Skills and CompetenciesTotal score (centered) x SDT: Autonomy (centered) on Willingness to adopt

term	estimate	std.error	statistic	p.value
(Intercept)	4.17	0.11	3.69E+01	3.65E-27
Skills and Competencies total (centered)	0.049	0.019	2.61	0.014
Autonomy (centered)	-0.033	0.058	-0.57	0.57
Skills and Competencies Total (centered) : Autonomy (centered)	0.0021	0.009	0.23	0.82

Table A18
Interaction effect Skills and CompetenciesTotal score (centered) x SDT: Competence (centered) on Willingness to adopt

term	estimate	std.error	statistic	p.value
(Intercept)	4.18	0.096	4.37E+01	1.97E-29
Skills and Competencies Total (centered)	0.039	0.016	2.45	0.02
Competence (centered)	0.23	0.069	3.3	0.0024
Skills and Competencies Total (centered) : Competence (centered)	-0.011	0.0084	-1.31	0.2

Table A19

Interaction effect Skills and Competencies Total score (centered) x CanMEDS: Knowledge/ Scientific (centered) changes on Willingness to adopt

term	estimate	std.error	statistic	p.value
(Intercept)	4.15	0.092	4.53E+01	6.78E-30
Skills and Competencies Total (centered)	0.055	0.015	3.62	0.001
CanMEDS Knowledge/ Scientific expected (centered)	-0.79	0.22	-3.58	0.001
Skills and Competencies Total (centered) : CanMEDS Knowledge/ Scientific expected (centered)	0.057	0.036	1.57	0.13

Table A20

Linear Mixed model of SDT Total x Skills and Competencies Total x CanMEDS Perceived Summed to predict willingness to adopt (not significant)

term	estimate	std.error	statistic	p.value
(Intercept)	4.11	0.14	29.25	5.55E-22
SDT total (centered)	0.046	0.046	1	0.33
Skills and Competencies Total (centered)	0.036	0.024	1.51	0.14
CanMEDS expected sums (centered)	-0.05	0.059	-0.84	0.41
SDT total (centered) : Skills and Competencies total (centered)	-0.0038	0.0056	-0.68	0.5
SDT total (centered) : CanMEDS expected sums (centered)	-0.005	0.017	-0.3	0.77
Skills and Competencies total (centered) : CanMEDS expected sums (centered)	0.01	0.011	0.98	0.33
SDT total (centered) : Skills and Competenciestotal (centered): CanMEDS expected sums (centered)	0.0019	0.00324	0.56	0.58

Table A21

*Top 10 rankings of Skills and Competences statements from Appendix B exercise per specialism orientation**

Specialism Group	Skill ID	mean rank	sd rank
Supportive	ID3	2.33	2.31
Supportive	ID8	2.33	1.53
Supportive	ID10	3.33	1.53
Supportive	ID7	5.33	4.16
Supportive	ID6	5.67	1.53
Supportive	ID2	6	3
Supportive	ID1	6.67	0.58
Supportive	ID5	7	3.61
Supportive	ID9	7.67	2.52
Supportive	ID4	8.67	0.58
Cognitive	ID4	2.64	2.01
Cognitive	ID9	2.82	2.44
Cognitive	ID3	4.91	3.14
Cognitive	ID6	5	2.05
Cognitive	ID5	5.18	2.64
Cognitive	ID8	5.91	1.64
Cognitive	ID1	6.55	1.51
Cognitive	ID2	6.82	3.46
Cognitive	ID10	7.09	2.95
Cognitive	ID7	8.09	1.7
Intervention	ID9	2.44	2.06
Intervention	ID4	3.81	2.37
Intervention	ID3	4.12	3.03
Intervention	ID2	5	2.45
Intervention	ID8	5.44	2.56
Intervention	ID6	5.62	1.86
Intervention	ID10	6.44	3.16
Intervention	ID5	7	2.68
Intervention	ID1	7.25	1.65

Intervention	ID7	7.88	2.25
Cognitive/Intervention combined	ID10	1	NA
Cognitive/Intervention combined	ID6	2	NA
Cognitive/Intervention combined	ID9	3	NA
Cognitive/Intervention combined	ID4	4	NA
Cognitive/Intervention combined	ID5	5	NA
Cognitive/Intervention combined	ID2	6	NA
Cognitive/Intervention combined	ID3	7	NA
Cognitive/Intervention combined	ID8	8	NA
Cognitive/Intervention combined	ID7	9	NA
Cognitive/Intervention combined	ID1	10	NA
Other	ID3	2.67	2.08
Other	ID8	3	1
Other	ID2	3.33	3.21
Other	ID9	3.33	2.08
Other	ID4	5	1.73
Other	ID5	5.33	3.21
Other	ID10	7	1
Other	ID6	7.33	2.52
Other	ID1	8.67	0.58
Other	ID7	9.33	1.15
Unknown	ID3	1	NA
Unknown	ID4	2	NA
Unknown	ID2	3	NA
Unknown	ID10	4	NA
Unknown	ID9	5	NA
Unknown	ID7	6	NA
Unknown	ID8	7	NA
Unknown	ID5	8	NA
Unknown	ID6	9	NA
Unknown	ID1	10	NA

*****_all ID descriptions except ID 1 and ID 10 can be found in Appendix B, with ID 1 being "recognizing and acknowledging mistakes" and ID 10 being "acting with an eye for the sustainability and efficiency of healthcare"_

Figure A4

Assumption checks for the main Multiple Linear regression model

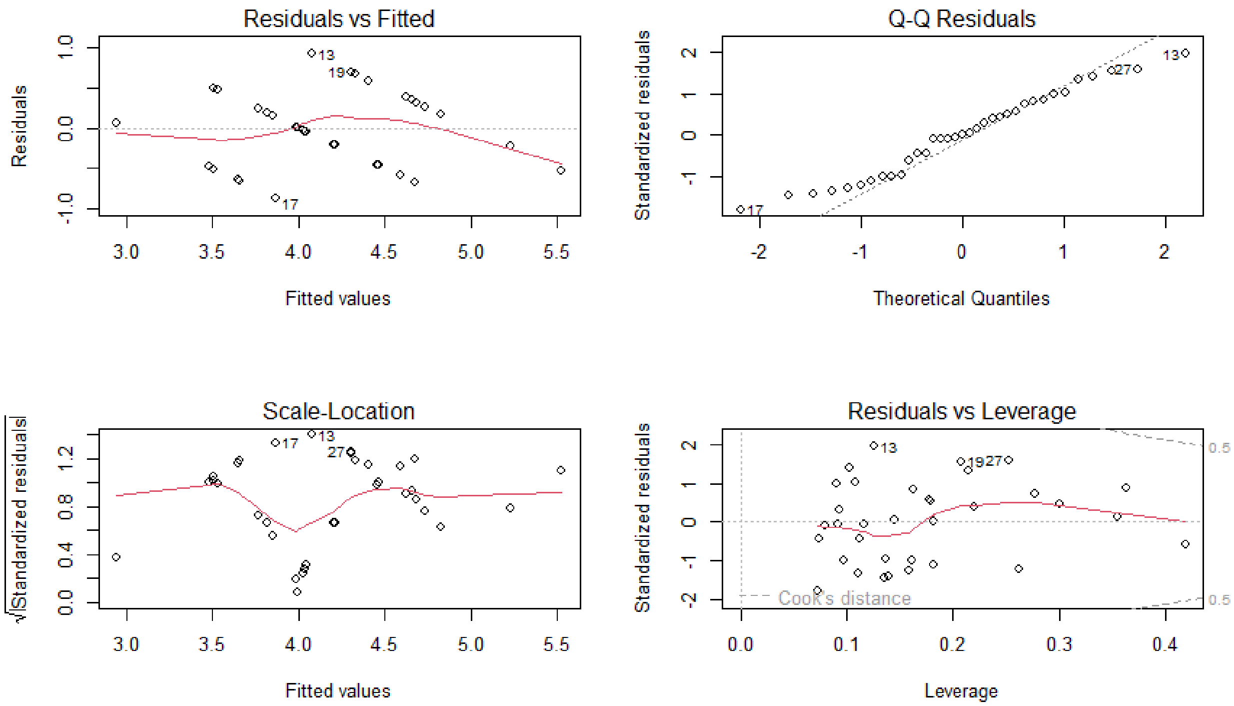

Figure A5

Assumption checks for the simple Multiple Linear Regression model

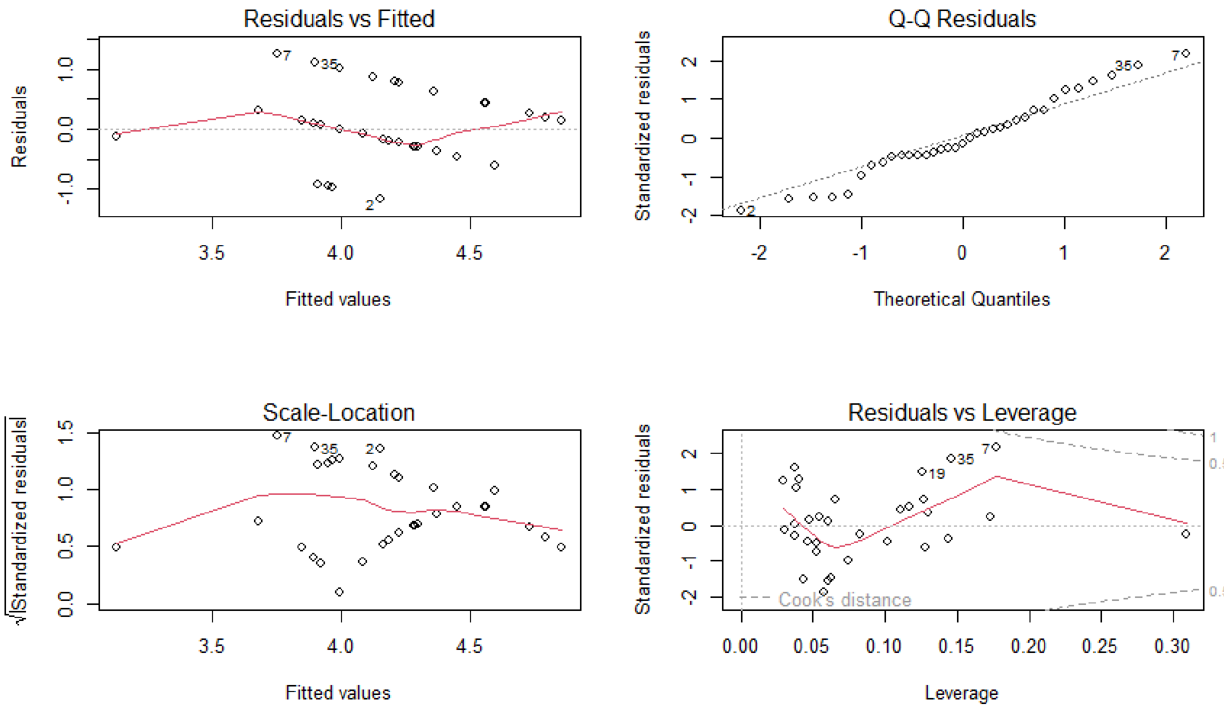

Table A22

VIFs of the Simple and the Main model

Predictor	Simple Model VIF	Main Model VIF
SDT	1.01	
Skills and Competencies	1.01	1.05
Autonomy		1.1
Competence		1.24
Expected Knowledge/ Scientific changes		1.2
Expected Professional Conduct changes		1.06

Appendix B: Qualitative Phase Ranking Exercise

Rank these 10 Skills and Competencies from most important (1) to least important (10) while thinking out loud about the reasoning behind your choices. The "ID" tags are the related ID's in the ranking assignment of the quantitative questionnaire.

(this did not come back in the ranking assignment of the questionnaire) Diagnostic Skills – The ability to make accurate diagnoses by analyzing symptoms and medical data.

ID 2: Decision-Making Under Pressure – Making quick decisions in critical situations with limited time and information.

ID 3: Problem-Solving Ability – Identifying complex problems and finding practical solutions.

ID 4: Empathic Communication – The ability to communicate with patients and their loved ones in an empathetic and effective manner, fostering trust and understanding.

(this did not come back in the questionnaire ranking assignment) Manual Dexterity and Precision – Physical skills such as precision and steadiness, essential in procedures like surgical interventions.

ID 5: Continuous Development of Knowledge – Striving for optimal quality and having the autonomous drive to keep developing.

ID 7: Quality Orientation – The pursuit of the highest possible quality, driven by intrinsic motivation to do the work well for its own sake.

ID 6: Reflective Skills – The ability to reflect on one's own actions and to learn from experiences, feedback, and new insights in order to continuously improve one's work.

ID 8: Engagement and Collaboration – Commitment to the work, the profession, and collaboration with colleagues, characterized by knowledge sharing and collegial support. Also includes engagement with patients and their loved ones.

ID 9: Ethically Responsible Conduct – Prioritizing the interests of patients or clients, with attention to integrity, altruism, and making value-driven choices.

Appendix C: Scales

Scale C1

Developed items of custom Skills and Competencies scale using a 5 point Likert scale (22 items)

1. Het leveren van zorg die bijdraagt aan het grotere geheel van doelmatige en houdbare zorg.
2. Het leveren van de hoogst mogelijke kwaliteit van zorg voor mijn individuele patiënten.
3. Bereidheid om in mijn vrije tijd met werk bezig te zijn (Bijvoorbeeld: administratieve zaken inhalen).
4. Individuele patiëntwensen afwegen tegen bredere maatschappelijke belangen, zoals kosten of duurzaamheid.
5. Regelmatig kritisch reflecteren op mijn eigen handelen en daar mijn scholing of bijleren op aanpassen.
6. Erkennen waar mijn kennis tekortschiet en daar actief iets mee doen.
7. Mijn kennis actief delen met collega's en bijdragen aan het leren van anderen.
8. Beschikbaar zijn voor collega's als zij ondersteuning nodig hebben, ook als het druk is.
9. Oog hebben voor de mens achter de patiënt en aandacht geven aan wat voor hem/haar belangrijk is.
10. Zelfstandig afwegingen maken in complexe situaties, op basis van mijn expertise en ervaring.
11. Passende zorg leveren, ook als dat betekent dat je moet afwijken van protocollen.
12. Op een empathische en begrijpelijke manier communiceren met patiënten en hun naasten.
13. Open en eerlijk communiceren met collega's, ook als het over fouten of onzekerheden gaat.
14. Mijn diagnostische keuzes baseren op zowel klinische ervaring als actuele richtlijnen en kennis.
15. Kalm en gefocust blijven tijdens situaties met tijdsdruk.
16. Handelen op basis van incomplete informatie, met vertrouwen op ervaring en inzicht (*Reverse coded)*
17. Verantwoordelijkheid nemen in complexe situaties en handelen op basis van inzicht en ervaring.
18. Creatief en flexibel omgaan met onverwachte situaties in de zorgpraktijk.
19. Het werk doen vanuit de overtuiging dat ik iets wil betekenen voor anderen.
20. Het werk blijven doen, ook als het zwaar is, omdat mensen op mij rekenen. (*Reverse coded)*
21. Met patiënten het gesprek aan durven te gaan als een behandeling medisch mogelijk is, maar maatschappelijk discutabel.
22. Verantwoorde beslissingen nemen in situaties van medische onzekerheid.

Scale C2

Developed items of custom Self Determination Scale for AI Adoption using a 5 point Likert scale (7 items)

1. (Competence): Ik voel me zelfverzekerd in mijn vermogen om AI effectief te gebruiken in mijn klinische werk.
2. (Competence): Het gebruik van AI zal mij helpen om me bekwamer en competenter te voelen als medisch professional.
3. (Autonomy): Ik heb het gevoel dat ik zelf kan bepalen hoe ik AI gebruik op een manier die past bij mijn klinisch oordeel.
4. (Autonomy): Ik heb de vrijheid om te beslissen óf en hoe AI mijn werk ondersteunt.

5. (Competence): Het gebruik van AI zal mij helpen om me meer verbonden te voelen met mijn patiënten of collega's.
6. (Autonomy): Ik ben bang dat AI mijn autonomie als arts aantast. (*Reverse coded)*
7. (Competence): AI heeft een negatief effect op mijn beoordelingsvermogen. *(Reverse coded)*