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Bridging the AI-literacy gap in healthcare: a qualitative analysis of the Flanders case-study

Christos Chatzichristos, Georgios Chatzichristos, Isabelle Boremans, Stefaan Gruyaert, Ilse De Vos, Maarten De Vos, Femke De Backere

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Christos Chatzichristos[1]; Georgios Chatzichristos[2]; Isabelle Boremans[1]; Stefaan Gruyaert[1]; Ilse De Vos[1]; Maarten De Vos[1]; Femke De Backere[3]

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Abstract

Background: The integration of Artificial Intelligence (AI) in healthcare is advancing rapidly, promising to enhance clinical decision-making, streamline administrative tasks, and personalize patient care. However, many healthcare professionals report a lack of confidence in understanding, critically evaluating, and ethically applying AI technologies. In regions like Flanders, Belgium—recognized for innovation yet facing moderate lifelong learning participation—these challenges are pronounced, especially amid an aging healthcare workforce and resource disparities between professions.

Objective: This study aimed to explore the requirements, obstacles, and prospects of AI adoption among healthcare professionals, and to identify the specific training priorities needed to bridge the AI-literacy gap in clinical practice in the Flanders region.

Methods: A multi-stage qualitative methodology was employed. First, 15 semi-structured interviews with key informants were conducted to inform the survey design. Then, a survey was distributed to healthcare professionals across Flanders, gathering 134 valid responses. Finally, three focus groups involving 39 participants were conducted to co-interpret the survey findings. Thematic analysis and descriptive statistics were used to synthesize insights across stages.

Results: Healthcare professionals recognized AI's potential to reduce administrative burdens and enhance clinical care but reported low self-perceived AI literacy, especially among older and non-physician staff. Interest in AI training was high, particularly for practical applications and basic AI knowledge, rather than technical coding or standalone ethics courses. Differences emerged based on occupation, age, and perceived job security. Nurses and younger professionals were especially concerned about the risks and opportunities of AI adoption. A lack of legally approved AI tools and practical hands-on training were identified as major barriers. Focus group discussions highlighted disparities in access to AI training between doctors and nurses, skepticism about private-sector-led courses, and the need for hospital management support in facilitating AI education.

Conclusions: A one-size-fits-all approach to AI training in healthcare is inadequate. Training programs must be stratified by occupation, age, and resource availability, emphasizing immediate practical applications while embedding ethical considerations within broader curricula. Addressing barriers to training accessibility and clarifying regulatory frameworks will be crucial to scaling AI integration in healthcare systems, starting in Flanders and potentially informing broader European initiatives under frameworks like the EU AI Act.

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Bridging the AI-literacy gap in healthcare: a qualitative analysis of the Flanders case-study

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Abstract

Background: Building on the assertion that nearly every clinician will eventually utilize Artificial Intelligence (AI), this study provides triangulated qualitative analysis of the requirements, challenges, and prospects for integrating AI into routine healthcare practice. This skills gap contributes to cautious and uneven adoption across clinical settings. Despite advancements, many healthcare professionals report a self-perceived lack of proficiency in comprehending, critically evaluating, and ethically deploying AI tools, which contributes to a cautious adoption in clinical settings.
Objective: While addressing key research questions, the study investigates the necessary prerequisites, barriers, and opportunities for AI adoption, and specific training priorities that medical staff require. The study is uniquely focused on the healthcare workforce, moving beyond the predominant emphasis in the literature on medical students.
Methods: Situated in Flanders, Belgium, a recognized innovation leader but with moderate lifelong learning participation, this research combines 15 semi-structured expert interviews, a regional survey of 134 healthcare professionals, and three co-interpretive focus groups with 39 stakeholders, all conducted in 2024.
Results: The results expose small generational and mainly occupational divides. For instance, 85% of survey respondents expressed interest in introductory AI courses tailored to healthcare, while 80% sought practical, job-relevant AI skills. However, only 13.8% of clinicians felt that their training adequately prepared them for AI integration. Notably, younger professionals (<30) were most eager to engage with AI but also more concerned about job displacement, while older professionals (>50) prioritized reducing administrative burden. Physicians and dentists reported higher self-assessed AI knowledge, whereas nurses and physiotherapists showed the lowest familiarity.The survey also revealed differences in preferred learning formats: doctors favored flexible, asynchronous learning, while nurses emphasized the need for accredited, employer-supported training during work hours. Ethics, though emphasized in academic literature, ranked low in training interest among most practitioners, except among younger and palliative care professionals. Focus group participants confirmed the need for clear regulatory guidance and access to accredited, practically oriented training. A significant insight was that nurses often lacked institutional support and funding for training, despite their pivotal role in AI-enabled workflows.
Conclusion: Taken together, these findings indicate that a one-size-fits-all approach to AI education in healthcare is unlikely to be effective. By triangulating insights across research stages, this study highlights the need for occupation-specific, accessible, and accredited AI training programs that

bridge gaps in digital literacy and align with practical clinical priorities. The qualitative insights obtained can inform policy and training priorities in light of the of EU AI literacy mandates, while highlighting persistent gaps in workforce preparation.
Keywords: AI literacy, Cross-disciplinary collaboration, Occupational divides, Structural inequalities, Tailored training, Lifelong learning, Upskilling

Introduction

The Information Age has spurred healthcare innovation by providing extensive data access and technology during the last 40 years, empowering the workforce to revolutionize healthcare. The emergence of Artificial Intelligence (AI) stands out as one of the most transformative elements of this era. Amid present conditions, AI technologies are increasingly becoming prominent in the analysis of diverse health data [CITATION Wan19 \l 1033]. They are accelerating the processes of diagnosis and therapy, enhancing imaging techniques, providing guidance for surgical procedures, and streamlining drug research, thereby enabling the development of more personalized therapies [CITATION Mat19 \l 1033].

In healthcare, AI has already shown remarkable promise, from analyzing chest X-rays and skin lesions (Keane and Topol, 2021) to increasing understanding of individual treatment response for COPD [CITATION Hut24 \l 1033] and significantly decreasing the time needed to review seizure events [CITATION Bha23 \l 1033] [CITATION Cha22 \l 1033]. Despite these advancements, scaling AI faces hurdles such as technical limitations, trust deficits, privacy concerns, algorithmic biases, and systemic issues like misaligned incentives, fragmented workflows [CITATION Esm24 \l 1033], or even lack of more general, basic data and AI literacy among healthcare professionals. Moreover, recent studies and frontline experiences reveal that stakeholder resistance (driven by concerns about professional autonomy, patient safety, and the opaque nature of certain AI systems) remains a substantial and persistent challenge[CITATION Mon24 \l 1033]. Regulatory frameworks remain in flux: despite the EU AI Act and other policy initiatives, many clinical environments still grapple with gaps in guidance, accountability, and the standardization of ethical and safety protocols. These realities contribute to a landscape where the transformative promises of AI are frequently counterbalanced by practical and institutional constraints, underscoring the need for nuanced, context-specific analyses of implementation[CITATION Kav24 \l 1033]. Addressing these challenges requires a strategic approach that emphasizes investments in human capital, clear regulatory frameworks, and improved data and AI literacy. To overcome these barriers, a human-centered design approach and revised frameworks tailored to healthcare-specific challenges are essential [CITATION Hua24 \l 1033].

One increasingly acknowledged, yet still under-researched, area where AI could provide significant support is the reduction of administrative burden in healthcare. Studies suggest that clinicians spend up to half of their working hours on documentation, scheduling, and other non-clinical tasks, leading to burnout and reduced time with patients[CITATION Adl20 \l 1033]. AI-driven solutions, such as automated note-taking, intelligent triage systems, and smart scheduling assistants, hold promise in alleviating this load. However, while the literature often emphasizes diagnostic and clinical decision-making applications of AI, the administrative potential of AI remains relatively underexplored in both academic and policy discussions. This gap limits the development of training programs and tools that target what may be among the most immediate and practical benefits of AI for the existing workforce.

Although the utilization of AI tools in clinical practice is on the rise, there exists a self-reported deficiency in the ability to comprehend, critically evaluate, and ethically utilize these tools in everyday clinical settings [CITATION Has23 \l 1033]. As a result, there is still an apparent reluctance by the medical workforce to utilise AI clinically [CITATION Doh24 \l 1033]. Given these contexts, an increasing number of researchers and organizations underscore the importance of

integrating AI into medical education, residency training, and continuous education programs for medical staff.

There is a well-documented gap in post-graduate and lifelong learning opportunities for healthcare professionals to acquire AI-specific skills, particularly compared to students[CITATION SMi23 \l 1033]. Systematic reviews have found that most AI training initiatives target medical students or early-career phases, while working professionals (especially nurses and allied staff) must often seek out fragmented or informal learning, with formal, occupation-relevant programs notably rare[CITATION JGa25 \l 1033]. While AI-related continuing education has expanded in theory, actual uptake remains low due to lack of system-wide support, limited funding, and time constraints among healthcare staff, as reported in a very recent Lancet Publication[CITATION Tim25 \l 1033]. This literature underscores that competency gaps in areas such as algorithm appraisal, ethical and legal application, and digital literacy persist well after graduation, risking uneven and sometimes unsafe AI adoption in clinical practice. These findings demonstrate the urgency and relevance of research focused directly on healthcare workers' lifelong learning needs and AI upskilling beyond academic education.

A survey found that only 13.8% of clinicians believed their training programs adequately prepared them for integrating AI into their practice [CITATION Kea21 \l 1033]. However, another survey [CITATION Sch21 \l 1033] shows that 71% of clinicians in ophthalmology, radiology, and dermatology reported optimism about AI improving their fields, particularly in disease screening and reducing monotonous tasks. This indicates that expectations for AI solutions are high among healthcare professionals. However, 80.9% had never used AI in practice, and only 5.5% rated their knowledge as "excellent". Interestingly, ophthalmologists reported the highest usage of AI (15.7%), compared to radiologists (6.1%) and dermatologists (5.2%), highlighting disparities in AI adoption between occupations that reflect differences in exposure and training [CITATION Sch21 \l 1033]. Significant divergences are also identifiable between different generations: clinicians with less than five years of experience were twice as likely to perceive AI's impact as profound compared to those with over 30 years of practice. This generational divide underscores the need for tailored strategies to foster acceptance and implementation.

The successful integration of AI into healthcare systems faces fundamental challenges, including user acceptance, consistent utilization in day-to-day operations, and seamless integration into the broader clinical workspace [CITATION Des24 \l 1033]. Overcoming these hurdles is essential to ensure that AI technologies become an integral and widely accepted part of routine medical practice. As in other non-medical professions, guidelines emphasize that training related to AI is crucial for its effective integration into everyday practice [CITATION Mal21 \l 1033], not only within pre-registration healthcare programs but also as a means of continuously developing the skill set of the existing workforce. While a growing volume of literature advocates for the inclusion of AI-related content in medical curricula [CITATION Mas19 \l 1033] [CITATION Meh21 \l 1033], the studies examining the training needs of the medical workforce in relation to AI are relatively scarce. [CITATION Doh24 \l 1033].

In line with these considerations, the current article explores the following research questions: *What are the requirements, obstacles, and prospects for medical staff in integrating AI into their daily tasks? What are their key priorities and needs for AI training in these areas?* To address these questions, the study conducts a thorough needs assessment of the overall medical workforce [CITATION Hea19 \l 1033]. The articles that have explored the training of the medical workforce in AI, have mostly concentrated on specific specializations such as clinical imaging [CITATION Doh24 \l 1033], or electrocardiogram interpretation [CITATION Tah23 \l 1033]. Few holistic approaches that explore the wide-scale AI deployment in healthcare practices call for investments in

human capital, clear regulations, and enhanced AI literacy[CITATION Esm24 \l 1033].

The current study leverages existing literature to implement multi-stage, qualitative research focusing on the healthcare professionals in the Flemish region of Belgium, a region that is characterized as an innovation leader - reflected in a comprehensive AI policy plan[1], but only moderate achievements in lifelong learning[CITATION Com24 \l 1033]. Accordingly, this focused investigation holds promise for enriching existing literature. The aim of this study is to systematically assess the prerequisites, barriers, and opportunities for AI adoption in healthcare, with a specific focus on identifying the training needs of the existing healthcare workforce in Flanders. Foregrounding AI literacy gaps within the healthcare workforce is particularly urgent, as the forthcoming EU AI Act will impose new obligations on providers and institutions to ensure safe, equitable, and competent AI adoption**.** The rest of the article is structured as follows. “Methods” Section delves into the relevant literature for the adoption of AI into Flanders and integration of AI training in the healthcare systems and presents the design and methodology of the current study. “Results” section illuminates the results from our research, while “Discussion” draws insights from the results and discusses limitations and pathways for future research.

Methods

Learning needs for AI in healthcare

An international survey [CITATION Bus24 \l 1033] of 4,596 medical, dentistry, and veterinary students from 48 countries found that 67.6% have positive attitudes toward AI in healthcare, and 76.1% desire more AI education in their curricula. Despite this interest, 75.3% reported limited general knowledge of AI, and indicated the absence of AI-related courses in their programs. Additionally, most respondents felt unprepared to use AI in their future careers, underscoring the necessity for curriculum enhancements to include AI competencies. The receptiveness of medical and dental students to AI applications is particularly indicative of how AI can be integrated into graduate training, preparing the next generation of healthcare professionals for a future deeply intertwined with technological advancements. Cross-sectional studies, involving 3,018 medical students across Turkey, further emphasized concerns about potential job reductions due to AI (44.9%), and the fear of AI devaluing the medical profession (58.6%). Along these lines, notably, only 6% of the respondents felt competent to inform patients about AI's features and risks, highlighting a significant literacy gap. In this vein, the majority expressed a need for training in AI applications, error reduction, and ethical problem-solving related to AI use [CITATION Civ221 \l 1033].

Similar studies (with smaller samples) confirm these findings and further underscore the necessity of incorporating practical and ethical AI training into medical education to prepare students for the realities of AI-supported healthcare [CITATION Wei241 \t \l 1033], Furthermore, experts emphasized the importance of integrating ethical considerations into AI education for medical students [CITATION Wei23 \t \l 1033]. In this regard, they advocated for a curriculum that balances technical AI skills with discussions on ethical implications, ensuring that future physicians can navigate the complexities of AI applications responsibly. This approach aims to foster a generation of healthcare professionals who are not only proficient in AI technologies but also mindful of their ethical responsibilities.

All the above indicate a pressing need to update medical education curricula to include comprehensive AI training [CITATION Kea21 \l 1033]. Such training should cover practical AI applications, ethical considerations, and strategies to mitigate potential negative impacts on the

[1] https://www.flandersai.be/en/beleidsplan-artificiele-intelligentie#:~:text=The%20Flanders%20AI%20Policy%20Plan,of%20roughly%20%E2%82%AC36%20million.

medical profession. By addressing these educational gaps, future healthcare professionals can be better equipped to integrate AI into their practice, ultimately enhancing patient care and maintaining the integrity of the profession. Moreover, medical education serves as the essential foundation for the entire continuum of healthcare workers' training. Refined curricula should also consider inconsistencies in AI training across institutions, highlighting the challenges of standardizing education systems globally [CITATION Ice22 \l 1033].

Contextualizing the study: an outline of Flanders' healthcare

The current study explores the integration of AI in healthcare training in Flanders, a region of Belgium, (NUTS1 statistical region[2]), which consists of five NUTS2 subregions, i.e. Antwerp (BE21), Limburg (BE22), East-Flanders (BE23), Flemish-Brabant (BE24) and West-Flanders (BE25). The healthcare system in Flanders is technologically advanced and operates under a mixed public-private model, offering universal coverage to residents. A network of hospitals, general practitioners, and specialists provide the care, which is mostly funded by social security payments. Primary care and preventative health services are highly valued in Flanders, with an emphasis on patient choice and accessibility.

Flanders' healthcare system, although resource-rich and technologically advanced, is facing challenges due to an ageing workforce that extends throughout the Belgian healthcare system. More analytically, Belgium's healthcare workforce is aging more rapidly compared to the EU average: the percentage of practicing physicians in Belgium that were aged 55 or older were 24,1% in 2000 and this percentage increased rapidly to 44,9% in 2016 surpassing the EU-12 average of 34,5% for the same year. Most recent data indicate that this trend continues, since in 2020 the percentage of Belgian physicians aged 55 and over was 43.3%, surpassing the EU-14 average of 35.1% and the EU-27 average of 37.4%. Against this background, several key specialties see an even higher proportion of aging practitioners, such as rheumatologists (46.1%), general practitioners (44.6%), and radiologists (41%). This aging workforce exacerbates existing shortages, straining the system's ability to meet the growing healthcare demands of an aging population. Despite efforts to address the issue, the percentage of older physicians in Belgium remains significantly higher than the EU-27 averages, posing a long-term challenge for healthcare sustainability[3].

Indeed, while AI is rapidly being adopted across the global economy, Flanders remains behind in this transformative shift. As of early 2024, an impressive 72% of companies worldwide reported using AI in at least one aspect of their operations[CITATION Sin24 \l 1033]. However, a more recent 2023 study from Flanders, indicates that only 32.1% of companies have embraced AI within their business processes[CITATION Sta24 \l 1033]. This difference underscores a need for greater awareness and integration of AI technologies in the region. One of the key challenges in Flanders is a lack of perceived necessity. A substantial 65.5% of Flemish companies believe that AI offers no significant benefits to their business. Compounding this issue, 64.5% admit to lacking the requisite knowledge, skills, and experience to effectively implement AI solutions. These barriers highlight an

[2] Nomenclature of territorial units for statistics, source: https://ec.europa.eu/eurostat/web/nuts

[3] https://www.healthybelgium.be/en/health-system-performance-assessment/sustainability-of-the-health-system/health-workforce-capacity

urgent need for targeted education and skill-building initiatives to bridge the gap between potential and practice. Although Flanders is recognized as a European innovation leader, it achieves only the European average when it comes to lifelong learning participation[CITATION Com24 \l 1033]. This was further confirmed by the Monitoring Report from the Flemish Department of Work and Social Economy [CITATION Ger24 \l 1033] . As the workplace continues to evolve, 95% of employers anticipate that the skills required of professionals will change significantly in the coming years. However, this shift is met with resistance: 40.7% of adults in Flanders currently do not participate in any form of training and express no interest in doing so, as they see no need for learning.

When asked about lifelong learning specifically related to AI, 44% of European respondents expressed scepticism, stating it is unlikely that their employer would provide AI-related training[CITATION Pou24 \l 1032]. This hesitancy creates a mismatch between the growing relevance of AI and the readiness of the workforce to engage with it. The European AI Act's Article 4 on "AI Literacy" could act as a catalyst for change [CITATION Eur24 \l 1033]. Starting from February 2, 2025, this directive requires "providers and deployers of AI systems to take measures to ensure, to the best extent possible, a sufficient level of AI literacy among their staff and other persons involved in the operation and use of AI systems." This legislative push will likely increase the demand for AI-focused training and education in Flanders, creating a significant opportunity for initiatives to close the AI literacy gap and foster a workforce that is ready to thrive in an AI-driven economy.

Overall, the Flemish context was selected because it combines a strong digital infrastructure and high levels of innovation performance with comparatively moderate participation in lifelong learning initiatives. This creates a unique setting in which both the opportunities and the structural barriers to AI adoption in healthcare can be examined in parallel. Moreover, the Flemish healthcare system is characterized by a dense network of providers and a diverse workforce, making it particularly suitable for exploring how AI integration may affect professionals at different stages of their careers. Finally, the region’s imminent obligations under the EU AI Act further underscore the urgency of assessing workforce readiness and advancing AI literacy, ensuring that the findings of this study carry both regional relevance and broader European significance.

Research methodology

The current study investigated the requirements, obstacles, prospects and needs for AI training for the healthcare workforce, by following an exploratory three-stage research design (see Initially, preliminary semi-structured interviews (Stage 1) were conducted to gather qualitative insights that informed the development of a subsequent survey (Stage 2). The survey was designed as an exploratory needs assessment and was not powered for statistical inference.In the third stage, focus groups were employed to co-interpret the survey results and extract deeper insights. This multi-stage approach ensured that the study addressed relevant, context-specific topics and was grounded in real-world perspectives. The study feasibility was assessed through VAIA’s coordination role, in terms of recruitment rates, participant retention, and completion rates at each stage of the study. Acceptability was evaluated, also via VAIA-facilitated feedback processes, based on participants’ ratings and qualitative comments regarding the relevance, clarity, and perceived applicability of the sessions. This study followed COREQ and CHERRIES guidelines; completed checklists are provided in Multimedia Appendices X and Y.). Initially, preliminary semi-structured interviews (Stage 1) were conducted to gather qualitative insights that informed the development of a subsequent survey (Stage 2). The survey was designed as an exploratory needs assessment and was not powered for statistical

inference.In the third stage, focus groups were employed to co-interpret the survey results and extract deeper insights. This multi-stage approach ensured that the study addressed relevant, context-specific topics and was grounded in real-world perspectives. The study feasibility was assessed through VAIA's coordination role, in terms of recruitment rates, participant retention, and completion rates at each stage of the study. Acceptability was evaluated, also via VAIA-facilitated feedback processes, based on participants' ratings and qualitative comments regarding the relevance, clarity, and perceived applicability of the sessions. This study followed COREQ and CHERRIES guidelines; completed checklists are provided in Multimedia Appendices X and Y.

Table 1 Research Design

Research Stage	Stage 1	Stage 2	Stage 3
Research Objective(s)	Gaining insights for the use of AI in healthcare	Knowledge, skills and training needs on AI in healthcare	Data integration & interpretation
Research Tool	Semi-structured interviews	Quantitative survey	Three focus groups
Research subjects/objects	Key informants and representatives of medical staff	Medical staff across Flanders	Medical staff across Flanders

More analytically, in the first stage of the study, the semi-structured interview guide was developed through an initial literature review on AI adoption in healthcare and digital training strategies [CITATION Kea21 \l 1033] [CITATION Esm24 \l 1033].The guide was subsequently refined in consultation with an expert panel consisting of three academic researchers and two clinical educators familiar with AI integration and adult learning in clinical settings. Fifteen (15) semi-structured interviews were conducted with key informants from the healthcare sector selected to represent diverse levels of AI expertise (see Error: Reference source not found). These individuals play a crucial role in shaping AI-related training strategies, curricula development, policy adoption, and institutional decision-making. Their inclusion allowed us to capture insights beyond clinical practice and reflect the broader ecosystem necessary for successful AI integration. The earlier stages of the study (interviews and surveys) were focused predominantly on frontline healthcare practitioners. The inclusion of non-practitioners in the focus groups during the final phase allowed us to validate, challenge, and expand the findings with institutional and educational perspectives, leading to more actionable conclusions. At the same time, given the co-interpretive nature of the final research stage, having a diverse group of stakeholders (including those responsible for educational programming, hospital-level innovation, and workforce development) aligned with our participatory research design and enhanced the practical utility of the findings.

A strategic sampling approach combined criterion sampling to target interviewees in pivotal healthcare roles and maximum variation sampling to ensure a broad spectrum of AI expertise. The incorporation of these methodological stages demonstrated the study's dedication to obtaining a comprehensive understanding of AI-related learning requirements while encouraging inclusiveness and usefulness in its conclusions. The aim was to explore the use of AI in healthcare within Flanders and to identify the existing AI training needs of the sector. The interview data were analysed using

thematic analysis [CITATION Bra06 \l 1033], supported by NVivo software to systematically identify themes: following the principles of grounded theory, coding proceeded in three iterative stages: open coding, in which transcripts were examined line-by-line to capture discrete concepts and assign initial codes; axial coding, where relationships among codes were explored and grouped into broader categories by linking subthemes and identifying patterns; and selective coding, which involved integrating these categories around central, overarching themes that addressed the research questions. Throughout the process, a constant comparison approach was applied within and across interviews to refine category boundaries and ensure analytic consistency. NVivo's memo and annotation functions were used to document coding decisions, emerging theoretical insights, and reflexive notes, creating an auditable record that enhanced the transparency and credibility of the analysis.

In line with qualitative research best practices, data collection for interviews continued until thematic saturation was achieved. That is, the point at which no new codes or themes emerged. Rather than relying on the rather loose criterion of no new data, we assessed theoretical saturation in terms of the completeness and depth of the analysis (Low, 2019). This point was reached after the 13th interview, with the final two interviews serving to confirm saturation without introducing novel concepts. Reaching this stage indicated that further interviews were unlikely to generate additional analytical insights, and thus informed the decision to conclude preliminary data collection at that point.

Interviewee	Background	Expertise on AI (scale 1-5)
Int1	General Practitioner	2
Int2	Logopedist	1
Int3	Research Nurse	3
Int4	Physiotherapist	4
Int5	Professor of geriatric psychiatry, psychotherapist	3
Int6	Professor Dentistry, Periodontologist	4
Int7	Professor of Cardiology and Head of Department	3
Int8	Associate Professor Urology	3
Int9	Cluster Manager Digital Health	3
Int10	Data Sciences Lead Pharmaceutical	4
Int11	Innovation Lead – Hospital	4
Int12	Self-Employed Home Care Nurse	1
Int13	Pathologist Hospital	1
Int14	General Practitioner	2
Int15	Professor of Internal Medicine and Engineering	5

Table 2 *Background of Interviewees and AI-Expertise level*

Building on the insights from the qualitative data, the study proceeded to design a survey aimed at conducting a comprehensive needs assessment [CITATION Civ22 \l 1033] across the regional medical workforce. The survey focused on several key areas: healthcare professionals' learning trajectories, their existing knowledge and skills related to AI, the impact of AI on their professional practices, and their specific learning needs regarding AI adoption. Developed using the EU Survey platform, the survey ran from July till the end of December of 2024. Prior to full deployment, the survey instrument underwent pre-testing with five healthcare professionals (two physicians, one

nurse, one health policy advisor, and one hospital IT coordinator) to ensure clarity, relevance, and usability of the items. Based on their feedback, minor revisions were made to improve question wording, reduce ambiguity, and streamline the Likert-scale design. Regarding psychometric evaluation, the section on importance-of-topics for AI training consisted of multiple items rated on a 10-point Likert scale. We conducted an internal consistency analysis for this group of items. The resulting Cronbach's α was 0.84, indicating good internal reliability of the scale.

The survey was digitally distributed to a wide array of healthcare organizations across Flanders, including four hospitals, five healthcare professional associations, four healthcare-focused SMEs and enterprise associations, six additional SMEs, two university medical schools via their alumni lists, and one NGO, viz. VAIA – Flanders AI Academy, with which five of the authors are affiliated. Additionally, the survey was shared through personal networks and disseminated via healthcare channels and conferences in the region. While this approach ensured broad and diverse reach, it also meant that the exact number of individuals who received or engaged with the invitation is unknown, making it impossible to determine a precise denominator or formal response rate. This limitation is a recognized challenge in non-probability, exploratory research, particularly when targeting hard-to-reach professional populations such as healthcare workers. To mitigate institutional bias, survey distribution relied on multiple independent networks beyond VAIA,the study does not aim for statistical generalizability but follows a qualitative, leaning, needs assessment approach, where the focus is on depth and diversity of perspectives , rather than representative prevalence estimates.

To mitigate the risk of non-response bias, we ensured diversity in occupation, age, and experience among respondents, and triangulated survey findings with insights from in-depth interviews and focus groups, enhancing the trustworthiness and validity of our conclusions. Despite extensive efforts, the survey yielded only 139 responses (see Table 3) from an estimated total population of 5,000 healthcare professionals, underscoring the challenges of engaging this demographic group in survey-based research [CITATION Hut19 \l 1033][4]. Five of the participants had filled less than 20% of the total questionnaire (more than 80% missing variables) and were excluded from the analysis, resulting in a final number of 134 respondents included in the analysis.

Healthcare professionals are a notoriously difficult group to engage in survey-based research due to time constraints, workload pressures, and survey fatigue [CITATION Hut19 \l 1033]. This is reflected in the survey responses (134 valid) which may appear limited in proportion to the estimated size of the target population (around 5.000 professional). While the challenges for engaging healthcare professions are well documented, the small sample still included a broad cross-section of healthcare roles across multiple regions in Flanders. This occupational heterogeneity enhances the analytical utility of the dataset. Most importantly, the survey was not intended as a stand-alone quantitative assessment but as part of a triangulated qualitative methodology that included in-depth interviews and focus groups. These multiple layers provided contextual richness and analytic depth that help counterbalance the relatively modest survey response rate. Along these lines, the primary aim of the survey was to conduct a needs assessment, not to generalize findings statistically. Therefore, this study is positioned within a qualitative research tradition, aligning with existing literature that frames basic survey statistics as supporting exploratory, interpretive aims rather than pursuing broad statistical generalizability [CITATION Cha23 \l 1033] Accordingly, the insights gained were intended to inform subsequent qualitative analysis and co-creation activities, rather than

[4] We need to note that EUsurvey website was offline for 10 days in the first weeks of September which we consider it a very important timeframe, since many potential participants returned from their holidays and multiple newsletters were shared.

to produce definitive conclusions about prevalence or distribution. This approach aligns with the growing emphasis on qualitative, reflexive research in the field of AI adoption, which has gained momentum in recent years [CITATION Cha25 \l 1033]. Nevertheless, we recognize that the survey results should be interpreted as indicative rather than statistically representative of the entire healthcare workforce. This limitation reflects both the exploratory scope of the study and the methodological challenges of capturing a rapidly evolving field such as AI in healthcare. Rather than aiming for generalizability, the survey was designed to generate insights, highlight emerging patterns, and guide the more in-depth qualitative inquiry. This recognition informed our decision to frame the study within an exploratory, qualitative-driven design, where the survey functions as a complementary entry point to contextualize and deepen subsequent analyses.

Table 3 *Demographics of participants in the Survey*

PARTICIPANTS			PARTICIPANTS		
Gender	Male	47 (35.07%)	**Seniority**	0-3	8 (5.6%)
	Female	83 (61.94%)		4-10	38 (26.57%)
	Other/NA	4 (2.98%)		10+	88 (58.74%)
Age	<30	16 (11.18%)	**Occupation**	Physician/ Doctor	45
	30-40	42 (27.37%)		Nurse/ Midwife	41
	40-50	34 (23.77%)		Manager	9
	50-60	34 (23.77%)		Dentist	8
	60-70	7 (4.9%)		Pharmacist	3
	NA	10 (7%)		Physio/ Kinesist	12
				Other [a]	16

[a] Including Podiatrist, Lab supervisor/geneticist, Radiographer, Medical Physicist, Biomedical Informatics (3), Clinical Trial Centre employee

In the final stage, three focus groups were conducted in December 2024, involving 39 medical practitioners, nurses, organizers of courses and lecturers each, to help with an inclusive and interpretive examination of the survey information gathered. The focus groups played a crucial role in analyzing the survey results, allowing stakeholders from the healthcare sector to validate key findings and translate them into concrete actions (see Table 4 in Appendix mapping high-level themes to illustrative quotations). Each session lasted approximately two hours and was structured around a semi-structured facilitation protocol that included (a) presentation of key survey findings, (b) guided discussion on their relevance and interpretation, and (c) open dialogue to surface additional perspectives or contextual nuances not captured by the survey. The facilitation was carried out by trained moderators of the core analysis team, with note-takers documenting group dynamics in addition to verbatim audio recordings. The discussions were transcribed in full and subjected to thematic analysis. Coding followed a hybrid approach, with an initial deductive framework based on survey-derived themes and policy priorities, complemented by inductive codes emerging from participants' reflections and narratives. Coding was conducted independently by at least two researchers per transcript, followed by iterative rounds of comparison, discussion, and refinement to enhance transparency and consistency. Inter-coder reliability was not treated as a purely statistical

exercise but as a qualitative consensus-building process, where discrepancies were discussed until agreement was reached on coding decisions. NVivo software supported the organization of codes, memo-writing, and linking of themes to illustrative quotations. This process ensured that the focus groups were not simply used as a validation step but as interpretive tools that added depth, nuance, and contextual grounding to the survey results. By capturing a broad spectrum of viewpoints and applying systematic procedures for facilitation and analysis, the study strengthened the credibility, rigor, and transferability of its findings.

This study was conducted in line with ethical standards for research involving human participants, it was carried out under the ethical framework of an ongoing approved project at the School of Political Sciences, Aristotle University of Thessaloniki (ethics approval number 237317/2024). In Phase 1, interviewees gave written informed consent; in Phase 2, survey respondents consented via an opt-in form, and no personal identifiers were accessed by the researchers (email handling for prize draws was done solely by a VAIA communication staff member). In Phase 3, all focus group participants consented to the use of anonymized ideas and images for scientific purposes. At no point were sensitive personal data collected, and all procedures were designed to ensure participant anonymity and voluntary participation. All consent materials will be made available upon request.

Results

Preliminary insights from key informants

In order to inform the design of the following research survey, the preliminary semi-structured interviews explored the opportunities and challenges of AI integration in healthcare. The interviews highlighted a collective emphasis on the need for (practice-oriented) AI literacy as an overarching concern, as well as the reduction of administrative burdens and ethical considerations arising from AI use as specific content-related issues. Not least, they highlighted references for learning modalities and the role of accreditation for healthcare workers. To actively engage healthcare professionals in relevant training, the most common argument was that AI tools need to provide practical benefits to their daily workflows, soon after their training. As one of the interviewees emphasized, "there will be more people interested when it is really practical, when you know how to use it in your daily practice" (Int_1). Similarly, another one pointed out that many professionals have "little time to really delve completely into something new," (Int_2) underscoring the need for tools that integrate seamlessly into existing systems. By implication, online courses were widely preferred, but they were perceived as coming with challenges, such as reduced engagement compared to in-person settings. Although many professionals preferred online learning for its flexibility, a researcher pointed out that specifically nurses often favor in-person training (Int_3). One way or another, the critical parameter for AI training integration that had to be explored was its contribution to the peoples' workload.

On this point, the most important potential contribution of AI that emerged from the interviews was related to the overwhelming administrative burden faced by healthcare professionals: the use of AI to automate repetitive tasks such as form completion and report generation was viewed as a promising solution. Most interviewees consented on the view that healthcare -and nursing, in particular - could benefit from AI tools to decrease the administrative burden and get more time for the patients. In this context, the head of a cardiology department highlighted that administrative tasks had grown over the years, reversing the time allocation between patient care and paperwork: "If I compare with 20 years ago, my focus was more than 80% on the patient and 20% on the administration. What we do see now is that it is just the opposite" (Int_7). In this context, several key informants shared the sentiment that saving time spent in administration could be the most critical

contribution of AI.

The shortage of time was related also to workforce shortages especially in nursing and psychiatry. Accordingly, AI's role in assisting with tasks that are increasingly difficult to manage due to workforce shortages "help make the job of a nurse easier to get care where it's needed" (Int_15). AI's potential to improve patient care was another focus area. From simplifying patient tracking to offering personalized health information, professionals identified various ways in which AI could benefit patients. For instance, someone stressed that "anything that can ensure that the patient is better informed and gets info tailored to them at the time they are ready" (Int_2) would be valuable. More information does not always come without challenges, as it can exacerbate the tendency to over-test, potentially tipping the balance further in favour of over-diagnosis, as one associate professor of medicine expressed his concerns (Int_8). This perspective highlights the need for careful consideration of the role of AI in healthcare to avoid unintended consequences. Rather than reducing administrative burden due to overdiagnosis, AI may ultimately enhance it.

In addition to this, AI's adoption brings inherent challenges, particularly regarding privacy, data security, and trust in opaque "black box" systems. A doctor underscored this issue, stating, "Everything that we helped validate or set up ourselves is fully trustable, but everything else developed as black boxes outside our environment, I don't trust at all" (Int_6). This skepticism underscores the importance of transparency and stakeholder involvement in AI development and deployment. Along this line, another interviewee emphasized the critical importance of using AI judiciously: while acknowledging its potential to assist with tasks such as language translation, he cautioned against over-reliance on AI systems, advocating for a balanced approach to ensure its proper application in diverse contexts.

These normative and ethical challenges raise the need for extensive training in order for the integration of AI in healthcare to come organically. Along these lines, many interviewees agreed on the importance of accredited courses for AI literacy. One of them noted that professionals are drawn to accredited programs because "they get points for the accreditation" (Int_6)[5]. However, these courses must directly impact clinical practice to attract interest. As another interviewee observed, "You need something that's directly influencing the practice before you go to a course" (Int_8). From a research perspective, the challenges and training needs of AI integration in healthcare must include well-structured training trajectories grounded in extensive, multidisciplinary research. This is where the current research survey plays a pivotal role, offering wide insights across diverse professional groups and healthcare settings.

Mapping AI training trajectories

Informed by the preliminary interviews with key informants, the second stage of this research utilized a survey to evaluate the learning needs and interests of healthcare professionals in Flanders regarding AI literacy in healthcare. The survey garnered responses from a diverse group, including doctors, nurses, and healthcare managers, revealing both a strong interest in AI literacy and significant gaps in existing knowledge and training.

More analytically, a significant survey indication was that AI knowledge levels vary across different professions. Managers, physicians, and dentists reported higher AI expertise, while nurses, physiotherapists and pharmacists showed lower familiarity (see Figure 3). This indicated that AI exposure is not uniform across medical fields, with some roles integrating AI more actively than others. Age played a crucial role in these variations also, as expected. Mid-senior professionals (40-50 years) reported the highest levels of AI knowledge, whereas older professionals (>60 years) had the least, with some indicating no AI expertise at all (see Figure 4). Responses from the 50-60 age group were mixed, suggesting varying degrees of AI exposure within this demographic, the 50-60 age group and the physicians exhibited the higher standard deviation in their replies. Contrary to

[5] In Belgium, many healthcare professionals must follow continuous professional development (CPD) to maintain their accreditation, which is legally required for some professions. This system ensures they stay up to date, and explains why they value training that aligns with their daily practice.

what was initially expected we can see that younger ages (<40) are not yet as familiar with AI, indicating the fact that AI is not yet part of the main curricula of

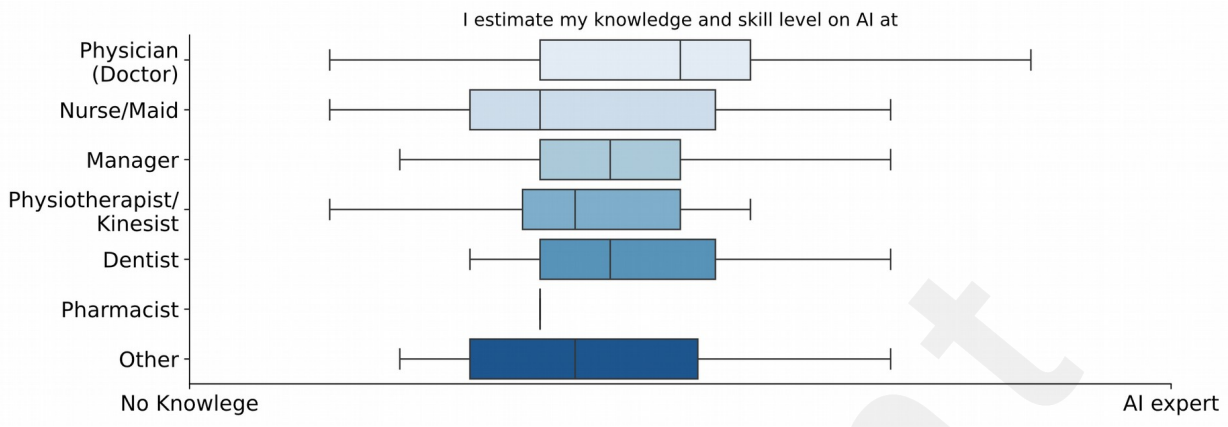

Figure 1 *Self-estimation of AI knowledge based on occupation*

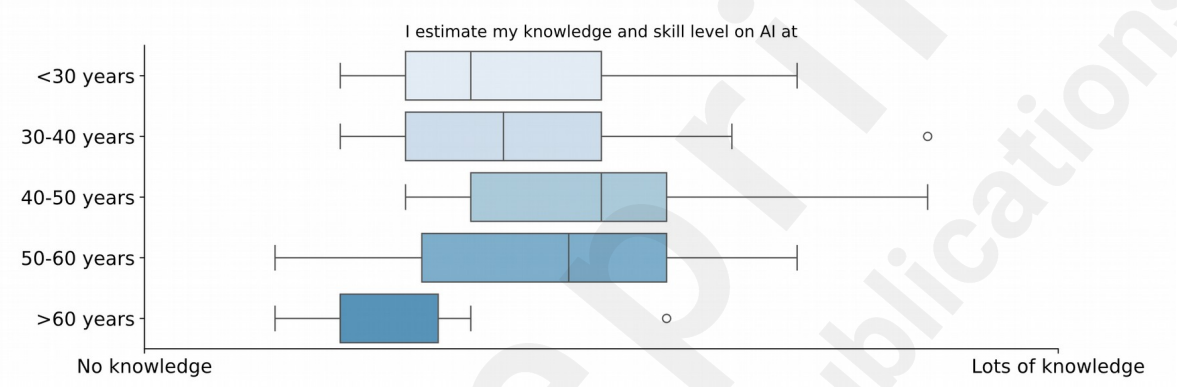

Figure 2 *Self-estimation of AI knowledge based on age*

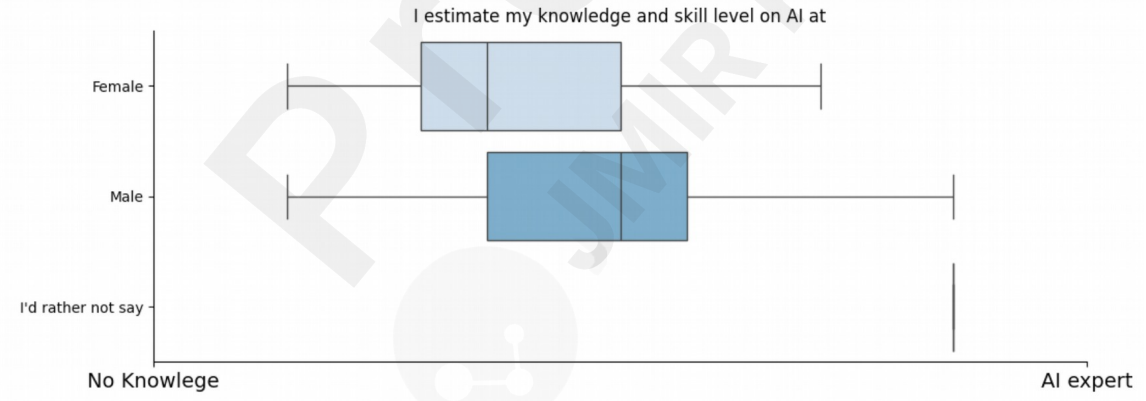

Figure 3 *Self-estimation of AI knowledge based on gender*

the universities in the healthcare faculties but a knowledge obtained by individuals in a later stage (either by post-graduate programs or by extra training courses). The only question where we observed a gender-based difference in responses was related to self-estimated AI knowledge (Figure 5). Male respondents generally reported higher self-estimations than female respondents. However, when analyzing responses within the same occupation, the differences disappeared. The overall gender disparity arises because our sample includes more female nurses (who tend to report lower AI knowledge self-estimations) and more male physicians, who report higher self-estimations. Therefore, the apparent gender difference shown in Figure 5 primarily reflect an occupational

disparity rather than a true gender-based variation.

Concerning the type of knowledge that the respondents would like to acquire for AI, most respondents prioritized “gaining basic AI knowledge” (74.64%), learning to “be able to facilitate the use of AI in my field (e.g. design a study, management, knowledge of ethics, etc.) - *no coding*” (70.29%), and “efficiently use pre-developed AI tools” (66.67%). Doctors and dentists were the two groups that were more interested (75.14% and 72.54%, respectively) in the facilitation of AI use in their field rather than the efficient use of pre-developed AI tools. Related to the exact topic of an AI course/training that they would like to follow, a significant majority of respondents expressed strong interest in an introductory AI course tailored to healthcare (85%), with nearly as many (80%) eager to acquire practical AI skills relevant to their field (see Figure 6). Learning priorities varied by age: younger professionals (<30 years) actively sought AI education, especially in decision-making and generative AI, while older professionals (>50 years) showed less interest in learning AI but acknowledged its role in reducing errors and improving patient confidence. The 30-50 age group balanced curiosity with concerns about practical implementation. These findings suggest AI education should be tailored for younger professionals and practical implementation strategies for older ones. The survey further highlighted a strong preference for immediately applicable AI tools over advanced technical expertise.

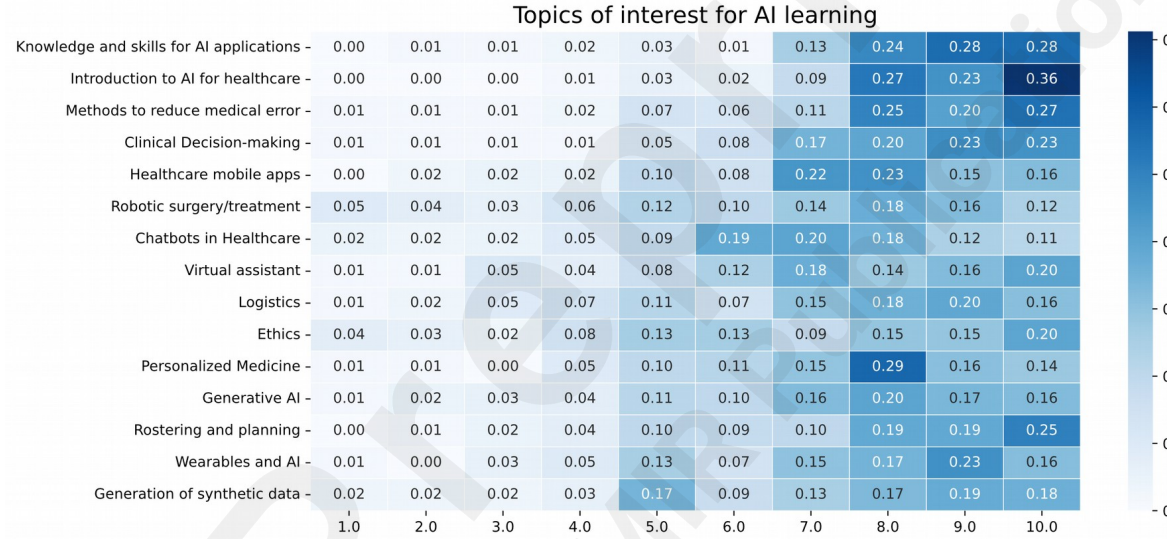

Figure 4 *Topics of Interest for AI learning (Likert Scale 1-10)*

No significant difference was noted between respondents of different gender, while again a variability of the choices based on the occupation has been identified. The two most interesting topics for almost all the occupations are the two first of Figure 6, “Knowledge and skills for AI applications” and “Introduction to AI for Healthcare”. For Nurses, though, “Rostering and planning” appears as the second most interesting topic (after the “Introduction to AI for Healthcare”), a topic which is much lower in the selection of the other occupations. “Personalized medicine” appears to be the third option for dentists, others and physicians (doctors), while “Methods to reduce medical error” appears more important for Managers, Nurses and Pharmacists. Another interesting finding is the fact that, contrary to previous studies [CITATION Civ22 \l 1033], the topic of “Ethics” is low in the interest of the respondents. The least interesting of the topics among almost all the groups (except for dentists, for which is penultimate) was the “Generation of synthetic data”.

Different occupations exhibited distinct patterns in their training preferences and frequency. Dentists and clinicians were the most engaged in continuous learning, with the majority attending training sessions at least once per month. In contrast, professionals in other occupations typically participated in training once every three months or less. When selecting a course provider or topic,

dentists, clinicians, and other healthcare professionals primarily trusted specialists in their respective domains, followed by their training institutions (universities or technical schools). However, physiotherapists and nurses prioritized recommendations from their employers over their training institutions. Managers stand out as the only group that places the highest trust in their employees' suggestions regarding the choice of courses, rather than relying on peers or experts in their field. Across all groups, social media and government recommendations play only a small role in influencing training choices.

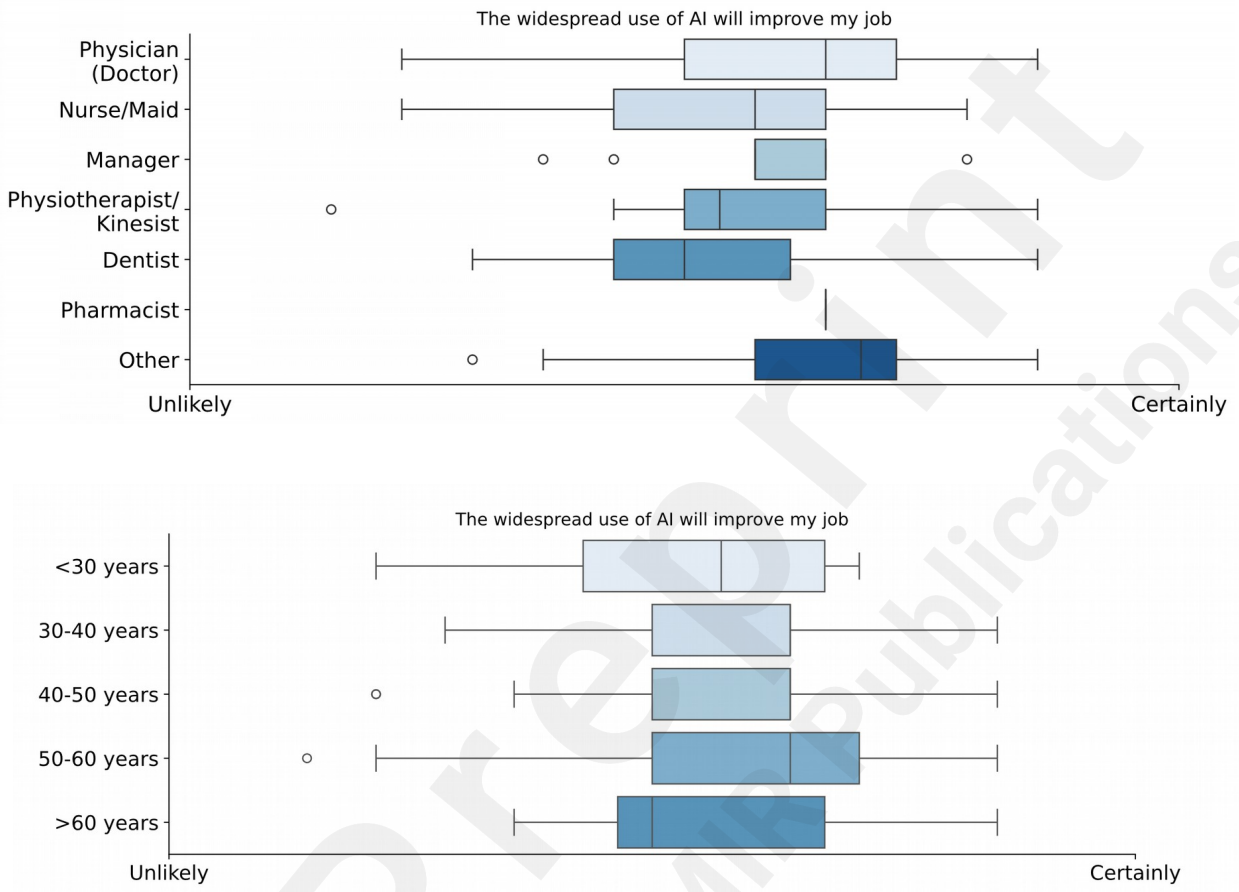

Figure 5 *Opinion about the*

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improvement that AI will bring into their job by occupation
Figure 6 *Opinion about the improvement that AI will bring into their job by age*

In parallel, perceptions of AI's impact on improving healthcare jobs varied by profession. Physicians and nurses were the most optimistic, while dentists and physiotherapists were more skeptical (see Figure 7). Managers and pharmacists held moderate to positive views. Similarly, younger professionals (<30 years) strongly believed AI would enhance their work, whereas older professionals (>50 years) were more cautious (see Figure 8). A notably greater standard deviation was observed also here among doctors and individuals aged 50–60 years, which may reflect the diversity of clinical specialties within these groups (such as cardiology, neurology, and others)that influence their experiences and attitudes toward AI integration. This heterogeneity suggests that field of practice could be a key moderating factor underlying the observed variability[CITATION Muh24 \l 1033]. Regarding AI's future in healthcare, professionals identified its greatest contributions as increasing patient confidence, reducing diagnostic bias, enhancing decision support, and improving access to healthcare information (see Figure 8).

An interesting finding of the survey was how healthcare professionals perceive the risk AI poses to their work. Again, AI perception in healthcare varied significantly by profession, age, and potentially gender. Dentists and pharmacists felt the highest risk of AI replacing their jobs, likely due to automation in diagnostics and prescriptions. Physicians and nurses were more confident, with a broader distribution of responses (see Figure 10). Age also played a role, as younger professionals (<30 years) felt more at risk, whereas older professionals (>50 years) were less concerned, although neither were not significantly concerned (see Figure 11). This generational difference suggests that younger professionals, entering a rapidly evolving workforce, may feel more vulnerable to technological changes, whereas older professionals, with more established careers, perceive AI as less of a direct threat.

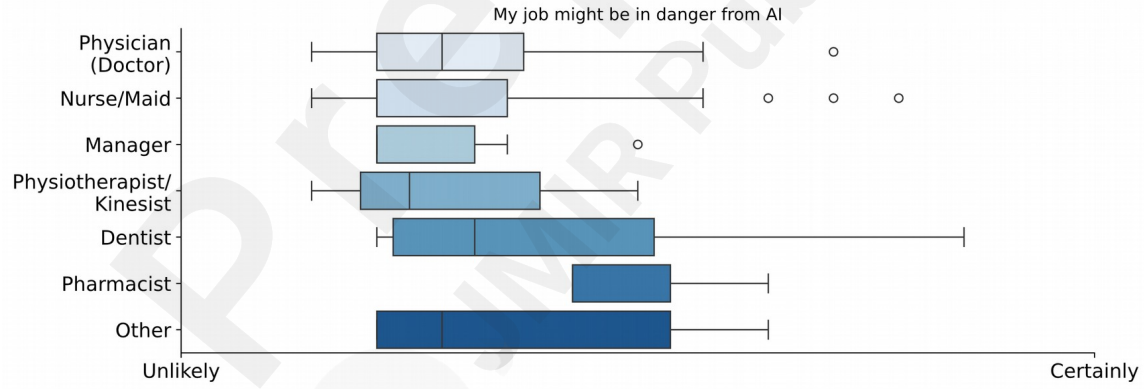

Figure 7 *Opinion of the participants by occupation, about the danger that AI might bring to their job.*

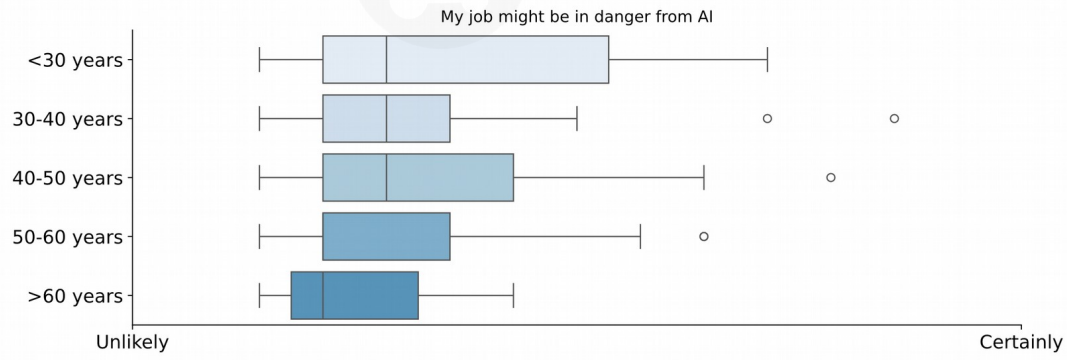

Figure 8 *Opinion of the participants by age, about the danger that AI might bring to their job.*

Younger professionals were more concerned about job displacement, likely, because they recognized AI's growing role in healthcare and wanted to stay competitive. This contrast reflects a mix of ambition and (modest) anxiety among younger professionals versus confidence and stability among older ones. As mentioned by [CITATION Web19 \l 1033] the impact of AI on employment may manifest more through reduced entry into occupations—fewer young people starting these jobs—rather than through increased exits by older workers, leading to a disproportionate effect on younger workers and this "entry margin" effect might be reflected in the answers of the participants. If you consider the answers based on the occupation, we can note that pharmacists and dentists are the two groups that were slightly more concerned about their job and believed that AI will improve their jobs less (see Figure 10 and 6, respectively).

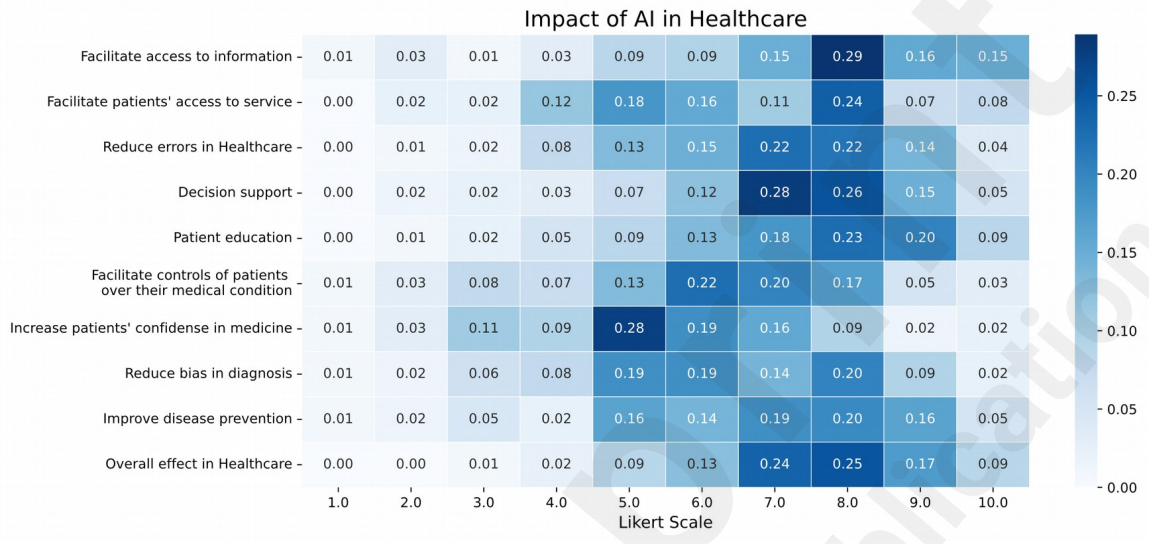

Figure 9

Impact of AI in Healthcare

The responses regarding the area where AI will have the greatest impact were quite diverse (see Figure 11). Participants generally agreed that AI would influence almost all the mentioned fields (access to information, patients' access to service, reduction of errors in healthcare, patients' education, control of patients over their medical conditions, reduction of bias in diagnosis, improvement of disease prevention and overall effect in healthcare). The only exception (or at least the area with the fewest responses based on the Likert score) was "increasing patients' confidence in medicine." The most significant areas of impact, though closely followed by others, were "facilitating access to information," "overall healthcare," and "decision support systems." Notably, no significant differences were observed across various demographic categories, including gender, age, occupation, or experience level.

Co-interpreting AI in Flanders' healthcare

The latest stage of this study focused on interpreting data through a collaborative framework of focus groups. A total of 39 participants took part in three focus groups, representing key stakeholders in healthcare and education, including lecturers from various disciplines (excluding practitioners), education and innovation hospital managers, representatives of nursing and radiology associations, and members of healthcare communities. To ensure efficient discussion and facilitation, the groups were structured as follows: 14 participants in the first group, 12 in the second, and 13 in the third. The focus groups were conducted in late December 2024, following a presentation of the initial survey results by the last author. Groups 1 and 3 were facilitated by the first author, while Group 2 was led by the last author (Groups 1 and 2 took place simultaneously following the "Split Groups Discussion" Methodology [CITATION RKr15 \l 1033]. Each group provided distinct perspectives on the integration of AI in healthcare, yet several overarching concerns emerged, particularly

regarding generational differences in attitudes toward AI, trust in technology, and the evolving role of healthcare professionals.

Each focus group provided unique perspectives on AI integration in healthcare, confirming several key survey insights while adding deeper practical and ethical dimensions to the discussion. Echoing survey responses, all three groups emphasized AI's role in reducing administrative burden, with particular interest in AI-driven

Table 4 Demographics of participants in Round Tables discussions

PARTICIPANTS			PARTICIPANTS		
Gender	Male	12 (30.76%)	**Occupation**	Manager	12 (30.77%)
	Female	27 (69.24%)		Lecturer	9 (23.08%)
Age	<30	1 (2.56%)		Nurses/Midwifes	4 (10.26%)
	30-40	9 (23.08%)		Physio/Kinesist	2 (5.13%)
	40-50	12 (30.77%)		Course provider	9 (23.08%)
	50-60	4 (10.26%)		Other	3 (7.69%)
	NA	13 (33.33%)			

solutions for documentation, scheduling, and workflow optimization. Discussions in the focus groups revealed a range of perspectives on AI in healthcare, with a particular emphasis on differences between professional groups, challenges in training, regulatory barriers, and disparities in available resources.

One of the central themes raised in the discussions was the difference between nurses and doctors in their access to and engagement with AI training. Participants noted that AI tools are primarily designed for doctors, while significantly fewer applications exist for nurses. This was seen as a major limitation, making it difficult for nurses to integrate AI into their daily routines. Additionally, nurses and doctors follow training at different times; nurses prefer courses during working hours and often expect compensation, whereas doctors tend to attend evening sessions. Some participants expressed frustration that funding for AI training is more readily available for doctors and research-oriented professionals, while nurses have far fewer opportunities.

A recurring concern was the difficulty of developing hands-on AI courses. Many participants pointed out that the most relevant knowledge on AI implementation resides within private companies, but these companies are not interested in creating educational programs, rather, their focus is on selling AI products. This dynamic created a gap in practical training, as healthcare professionals needed guidance on AI applications but did not trust company-led training initiatives, rather than courses coming from universities. A few participants mentioned that radiologists were an exception, as companies do provide AI training in collaboration with the Radiology Society. However, in most other fields, there was a clear demand for co-created courses where universities and companies work together to ensure both credibility and relevance.

Another major topic discussed was the regulatory complexity surrounding AI in hospitals. Participants frequently emphasized that many AI tools were not allowed to be used in clinical practice, creating uncertainty about what is permitted. There was a strong sentiment that hospitals need clearer guidelines and policies to help professionals navigate AI implementation. Some participants felt that the lack of clarity leads to hesitation, making AI adoption slower than it could be.

Time constraints for training were another issue raised in the discussions. Doctors, especially those in private practices, had more flexibility in choosing when to follow AI courses, while nurses required training during work hours, which limited their opportunities. There was agreement that hospital management plays a crucial role in ensuring *all* healthcare professionals, not just doctors,

have access to AI education. Several participants pointed out that doctors, who often earn more by seeing more patients, may have a financial incentive to adopt AI tools that improve efficiency, while nurses, who work on fixed salaries, focus more on how AI can support patient care and workflow improvements (supported also by the survey and their interest in courses related to Rostering and Planning). Participants also discussed the general lack of resources for AI education. There was widespread agreement that funding constraints made it difficult for hospitals and universities to develop robust training programs, especially for lifelong learning. Some attendees noted that universities tend to focus on AI education for students rather than professionals, as resources are limited, and institutional priorities are not always aligned with the needs of the workforce. A broader issue raised in the discussions was the lack of ready-to-use AI tools in clinical practice. Many participants emphasized that healthcare professionals need AI solutions that can be integrated immediately into their workflows, yet such tools are not widely available. Some expressed frustration that AI was often presented as a future technology rather than something that can help them today. Others pointed out that existing AI training often focuses on theoretical knowledge rather than practical applications.

A particularly interesting discussion arose around ethical considerations. While ethics courses are often integrated into broader AI programs, the focus groups revealed a clear generational divide in how participants approached AI ethics. Some participants pointed out that younger professionals, particularly students, tend to prioritize ethical concerns, (as has also been pointed by previous studies contacted with students[CITATION Civ22 \l 1033]) whereas professionals in the workforce are more focused on AI as a functional tool. A common argument was that healthcare workers simply do not have the time to engage deeply with ethical discussions in their daily routines and believe that ethical concerns should primarily be handled by AI developers. However, there were diverging views within the groups. One participant argued that financial incentives drive much of the AI interest in healthcare, particularly among doctors who earn more with increased patient volume. In contrast, another participant from a postgraduate palliative care clinic shared that ethics was a major focus in their discussions, suggesting that ethical concerns become more prominent in fields dealing with sensitive end-of-life care. This small disagreement highlighted that while some professionals may deprioritize ethics, others see it as essential depending on the context in which AI is applied.

Across all three groups, discussions highlighted a complex and evolving landscape for AI adoption in healthcare. In Table 4 the key cross-cutting themes (ie. administrative burden, ethics, training logistics, trust, generational and occupational differences) can be viewed. It illustrates how each was supported by data from interviews, surveys, and focus groups. While there was general recognition of AI's potential, participants made it clear that their trust, learning needs, and expectations vary significantly based on their profession, work environment, and access to resources. Addressing these concerns will require targeted training strategies, clearer regulations, and better collaboration between academia, industry, and healthcare institutions.

Table 5 Joint display of the cross-cutting themes in the three different phases of the study (ie., inverviews, surveys, and focus groups).

Theme	Interview Insights	Survey Findings	Focus Group Insights
Administrative burden	Viewed AI as a potential tool to reduce time spent on documentation	Identified as a high-impact area for AI use, especially by nurses and mid-	Strong consensus that administrative relief is AI's most practical benefit in

	and form-filling.	career professionals.	the short term.
Ethical concerns	Raised, but often secondary to practical concerns. Some distrust in “black box” systems.	Ethics ranked low in topic interest; especially low among clinicians.	Disagreement between participants. Opinion for decreased importance of ethics once you graduate and start working. Whereas palliative care workers emphasized ethical sensitivity.
Training logistics	Online preferred for flexibility, but in-person better for engagement; nurses need compensated training. Call for accredited courses.	Minor variability among different age and occupation. Everyone wants accredited courses.	Gaps in training availability noted, especially for nurses; call for accredited, hands-on programs.
Trust and transparency	AI developed in-house seen as more trustworthy than external, opaque systems.	Trust in AI lower among older and non-clinical respondents; survey shows moderate optimism but limited usage.	Professionals want clearer regulatory guidelines; co-development seen as way to build trust.
Occupational differences	Nurses need AI for workflow; doctors focus on diagnostics;	Clear role-based differences in learning needs and perceived usefulness of AI.	Frustration over unequal access to training funding; nurses feel underserved.
Generational differences	Not observed	<30 age group most interested in learning AI; >50 least engaged but acknowledge AI benefits.	Generational divide on ethics, tool adoption, and openness to innovation.

Discussion

The current multifaceted, qualitative study provided a nuanced view of both opportunities and challenges in integrating AI into healthcare. The study showed that while the vast majority of respondents recognized AI's potential to improve efficiency it also revealed a complex relationship between age, occupation, resource availability, and attitudes towards AI in healthcare. Younger professionals, non- physicians, were generally more concerned about AI potentially replacing jobs, yet they remained more positive about using AI in their work. This dual perspective is likely linked to their limited access to resources, such as institutional support and opportunities for professional development and the fact that AI is not yet implemented in the bachelor programs of any (para) medical university/school in Flanders. Early-career professionals, facing restricted resources and administrative pressures (especially non-physicians), may see AI as a valuable tool to alleviate

workload and enhance their capabilities, making them more eager to integrate AI into their practice despite concerns about job security. In contrast, older professionals (>60 years) appear less concerned about AI replacing jobs but are more skeptical about actively using AI. This skepticism may stem from their well-established positions and greater access to resources, including institutional support, funding, and established networks, which reduce their perceived need for AI. Having navigated the early stages of their careers, they may feel less urgency to adopt new technologies, especially when their roles are more secure and supported. Essentially, their (more) resource-rich environment provides them with stability, reducing their perceived risk from AI but also limiting their motivation to engage deeply with new technology. These observed generational and occupational divides directly inform our proposed multi-tiered strategy: younger, resource-constrained professionals call for subsidized and practice-oriented training schemes, while older, resource-secure professionals highlight the need for embedding AI within existing continuous professional development (CPD) frameworks rather than new standalone programs. By explicitly mapping these divides to differentiated policy interventions, we ensure that recommendations are grounded in lived workforce realities.

Occupations in healthcare show varying levels of exposure to AI. Clinicians such as radiologists and lab technicians face high exposure due to AI's growing capacity for data analysis and pattern recognition. In contrast, roles like nurses and care managers(where social intelligence, adaptability, and hands-on judgment are essential) are less exposed and more resilient to automation. This does not mean clinicians are at risk of replacement, but rather that their tasks are shifting. To stay relevant, they will need to adapt by integrating AI into their workflow, focusing on what AI cannot do: contextual reasoning, communication, and ethical decision-making. Meanwhile, roles with strong interpersonal and organizational components may see their value reinforced, provided they also adapt to AI-enhanced systems [CITATION Lan21 \l 1033]. While AI adoption might hold the potential to promote fairer resource allocation, offering individuals in socio-economic constraints enhanced access to knowledge, skills and opportunities. the very same groups might be also more vulnerable to job displacement and precarity, as AI-driven transformations may exacerbate existing inequalities rather than alleviate them. The uneven trust and adoption patterns we observed across age and occupational groups illustrate how digital divides are reproduced within the workforce itself, making equity considerations not only a systemic policy concern but also an empirically grounded outcome of our study. This alignment between our data and broader digital equity debates underscores why workforce training cannot be designed as a "one-size-fits-all" model but must instead be differentiated by age, occupation, and institutional support.

These findings are embedded within a broader discussion on digital health equity. The digitalization of healthcare carries the risk of deepening existing health and social inequities if not accompanied by deliberate, equity-oriented policy frameworks. As digital tools increasingly mediate access to services and reshape clinical workflows, the potential for exclusion becomes particularly acute among already marginalized groups. This has been observed in multiple contexts, including the Netherlands, where digital care policies are framed as progressive and universally beneficial, yet structural risks, such as disparities in digital literacy, socioeconomic access, and institutional support, receive limited attention [CITATION Coe25 \l 1033]. Such gaps reflect what has been described as a policy "blind spot" [CITATION Coe25 \l 1033]: the tendency to depoliticize digital care and detach equity considerations from discussions of infrastructure and governance. In contrast, the present study's results resonate with research highlighting digital literacy training as a core enabler of equitable digital health [CITATION Wil24 \l 1033]. This perspective treats digital health, including data and AI applications, not as a neutral technological progression but as a socially embedded transformation shaped by uneven resource distributions, institutional priorities, and workforce dynamics. For example, Danish digital health policy has struggled to reconcile legal commitments to equality with the realities of digital stratification [CITATION Eri23 \l 1033]. Similarly, the Flemish context illustrates how even innovation-leading regions may fall short in translating ambition into

inclusive practice. In this light, digital health equity must be approached as a governance concern, not merely a design feature. In our case, the absence of these enabling conditions -particularly tailored training and institutional recognition of diverse learning needs-contributed to uneven levels of trust in AI and unequal adoption patterns. Nurses emphasized rostering and workflow integration, while physicians and dentists were more focused on clinical facilitation. Yet few training initiatives accounted for these differentiated needs. This occupational stratification reflects broader patterns of digital exclusion described in the literature, where standardized solutions fail to address context-specific barriers [CITATION Ric22 \l 1033]. By explicitly linking these findings to policy debates such as the EU AI Act, our study shows how occupational and generational inequities in AI adoption mirror broader structural risks, reinforcing the urgency of equity-driven governance frameworks.

Along these lines, we propose a multi-tiered strategy aligned with key stakeholder roles. First, healthcare institutions (e.g. hospitals, professional associations) should embed mandatory data & AI literacy modules into existing CPD frameworks, ensuring these are accredited, occupation-specific, and available in both online and in-person formats. Training content should prioritize practical integration (e.g. rostering tools, triage systems, clinical decision support) and include embedded ethical scenarios rather than separate ethics modules. Second, regional health authorities and ministries should establish targeted funding schemes that enable subsidized training for under-resourced staff groups (particularly nurses), and early-career professionals. These schemes should recognize the structural disadvantage some groups face in accessing non-compensated learning time. Also, by providing equal chances to AI literacy for all healthcare professionals will improve the qualitative adoption of AI systems. Parallel to this, employers should be incentivized (e.g. via tax credits or public grants) to allocate protected time for (data and AI) training during work hours.

Third, academic institutions and universities should co-develop interdisciplinary AI education tracks in collaboration with clinical partners and technology developers. These tracks should offer micro-credentialing (as came out from our study since accreditation was a request) pathways and include hands-on exposure to real-world AI tools, ideally integrated into existing clinical education curricula to reduce learning redundancy. While concerns regarding the ethical implications of AI in healthcare were frequently raised, ranging from bias in AI algorithms to patient data privacy, there was surprisingly little interest in dedicated training programs focused solely on AI ethics. This discrepancy suggests that while ethics remains a key concern, it is not seen as an immediate priority for skill development among healthcare professionals, who are more focused on practical AI applications and workflow integration. Given this reality, embedding ethical considerations within broader AI training, rather than presenting them as standalone courses, may be a more effective strategy. By integrating discussions on bias, transparency, and accountability into technical and clinical AI education, ethics can become a natural part of AI adoption rather than an isolated, optional subject. This approach ensures that healthcare professionals develop a nuanced understanding of AI's ethical challenges while remaining engaged in training that aligns with their immediate professional needs. This generational and occupational divergence helps explain why ethics was acknowledged as important yet deprioritized in practice: for younger professionals facing immediate workload pressures, applied utility outweighed abstract ethical debates, whereas older, more established professionals expressed skepticism rooted in systemic trust and governance issues. Importantly, this divergence supports our recommendation to embed ethics within practice-oriented modules, ensuring that ethical reasoning develops in parallel with technical competence rather than in isolation.

Fourth, technology providers must be engaged as co-designers of training, but under strict ethical and regulatory oversight. Partnerships with trusted educational bodies (e.g. medical colleges, nursing federations) can help mitigate bias and ensure neutrality, while also fostering greater clinician trust in AI tools. Finally, to overcome the fragmentation in training provision and ensure inclusivity, we recommend establishing a regional AI training coordination body, led by health ministries or national digital health agencies, which would curate, accredit, and evaluate AI-related

training offers across providers, occupations, and settings. By operationalizing these stakeholder-specific roles, training efforts can be scaled in a way that reflects real-world needs, acknowledges occupational and generational divides, and upholds digital equity as a core principle of health system innovation.

By placing our findings within the broader discourse on digital health equity, we echo recent calls for a multi-level approach to digital transformation, one that embeds structural awareness into both policy development and training implementation. Without such a shift, digital care risks reinforcing the very disparities it promises to address, particularly as regions prepare for the rollout of EU legislation such as the AI Act, which will impose new obligations on providers and deployers to ensure AI literacy. Given the uneven starting conditions, regional health authorities and ministries should act first by establishing funding schemes and coordination bodies to reduce disparities in access to AI training. This creates the enabling environment in which healthcare institutions and employers can embed structured training into CPD frameworks. Building on this foundation, universities and technology providers can co-develop and scale interdisciplinary, practice-oriented modules under clear ethical oversight. Our study thus contributes not only to the literature on AI integration in healthcare but also to the wider debate on how to build equitable digital futures in health systems already marked by occupational, generational, and structural divides.

Concerning limitations of our study we reckon that the findings are exploratory and based on a non-probability sample, which means they should be interpreted as indicative rather than representative. The focus on the Flemish context also limits the transferability of results to other healthcare systems. Moreover, the rapidly evolving nature of AI in healthcare means that attitudes and readiness may shift over time. At the same time, participation may have been skewed toward individuals with strong opinions, either highly enthusiastic about AI or skeptical of its role in healthcare, potentially underrepresenting the broader, more neutral majority. Given an estimated distribution[6], we recognize that our sample overrepresents physicians, nurses, and dentists relative to their actual proportions in the healthcare system and underrepresents allied health professionals Furthermore, the relatively limited number of respondents constrains the ability to conduct robust analyses of intersectional factors, such as examining smaller subgroups defined by combinations of profession, age, or other demographic variables. This limitation reduces the statistical power and granularity needed to uncover nuanced trends within these intersections.This imbalance likely reflects a response bias, as physicians, nurses, and dentists are more frequently targeted in institutional mailing lists and professional networks and may also be more accustomed to participating in research or policy consultations. In contrast, allied health professionals often have less visibility in centralized databases and may face greater workload or institutional barriers that limit their participation in voluntary research studies and probably also training. Future research should therefore build on these insights through larger-scale and comparative studies, as well as longitudinal approaches that capture changing dynamics.

Crucially, the findings suggest that a one-size-fits-all approach to AI training is inadequate. Instead, future learning trajectories must be stratified by occupation, age, and available resources, and they should prioritize hands-on applications over theoretical content. Embedding ethical considerations into practical modules, rather than isolating them, may also bridge the current disconnect between ethical awareness and perceived learning relevance. As Flanders prepares for the implementation of the EU AI Act, this research highlights a timely opportunity to co-create inclusive, accredited, and accessible AI training programs that reflect the lived realities of healthcare professionals. Doing so will be essential not only for scaling AI integration locally but also for

[6] Comprehensive and up-to-date statistics detailing the full distribution of healthcare professionals by occupation specifically for the Flemish region are not publicly available in an aggregated format. Nurses (~45–50%), physicians (~15–20%), dentists (~2–3%), allied health professionals including physiotherapists, occupational therapists, imaging technologists, laboratory staff, etc. (~25–30%). [CITATION Riz \l 1033][CITATION Sta23 \l 1033] [CITATION RIZ23 \l 1033]

informing broader efforts to build an equitable, AI-ready healthcare workforce.

Author Contributions

CC, GC, IB and FDB conceived the study. CC performed all the interviews. CC, GC, IB, SG, IDV and FDB prepared the questionnaire. CC and FDB lead the discussions during round of table sessions. CC and GC performed the data analysis. IDV, IB, MDV and FDB contributed to the interpretation of results. MDV provided domain expertise and revised the manuscript. All authors read and approved the final manuscript.

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We also sincerely thank all the interviewees and the participants who completed the questionnaires and contributed actively during the round tables. Their openness and engagement made this research possible.
The authors' affiliation with VAIA (Flanders AI Academy) did not influence the study's findings or policy recommendations. Importantly, the necessity of AI training itself was not under debate in this research; rather, discussion focused on the specific format, content, and delivery of such training to best match stakeholder and workforce needs. VAIA's mission is centered on lifelong learning in technology -including but not limited to AI-, with no bias toward any particular training model, provider, or technological focus. Furthermore, we acknowledge the use of AI tools to support the development of this manuscript. The transcription of the interviews was facilitated by the Microsoft Teams AI assistant, while ChatGPT was used to improve the language and clarity of the introduction.
The dataset generated and analyzed during this study from the survey is available from the corresponding author on reasonable request.

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Appendix

Mapping of Focus Group Themes to Illustrative Quotation

Theme	Representative Quote	Focus Group / Participant
Practical integration of AI	“You need something that's directly influencing the practice before you go to a course.”	FG2 – Senior physician
Inequities in training access	“Nurses want training during work hours, but we often don’t get the same funding or flexibility as doctors.”	FG1 – Nurse association representative
Trust in AI tools	“If we didn’t co-develop it, I don’t trust it. These black-box systems worry me.”	FG3 – Academic clinician
Regulatory and	“We don’t even know what’s allowed yet.	FG1 – Innovation

Theme	Representative Quote	Focus Group / Participant
legal uncertainty	Hospitals are waiting for clear policies before using these tools."	manager
Ethical concerns and generational divide	"Students are very concerned about AI ethics. In real-world practice, we just need something that works for patients."	FG2 – Clinical educator
Resource limitations in AI rollout	"Universities are not equipped to train the workforce—resources are going to pre-service education, not to professionals."	FG3 – Medical school lecturer
Differences in motivation by profession	"Doctors are looking for time-saving tools; nurses are asking how AI can support patient care more directly."	FG1 – Hospital training coordinator

APPENDIX

If your answer is yes for any of the questions 17, 18 and 19, please write down your email (we will not use this information for any other purpose than those explicitly mentioned in either question 17, 18 or 19).

According to the new data protection guidelines in the European Union, your approval is needed to allow us to use the data of your questionnaire. Data will be used for scientific use only. Do you agree to allow us, VAIA, to use your statements for scientific use? (Please note, if you select "no", your answers cannot be used and will be deleted immediately.)

- Yes
- No

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