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Perceptions of AI competence in social and healthcare services: Readiness, reliance and realism

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Abstract

Artificial intelligence (AI) is transforming the health and social service environment through increasingly advanced and autonomous digital solutions. AI competence is recognized as an emerging dimension of digital competence, leading to a growing demand for AI-related skills among health and social service professionals (HSPs). In this study, AI competence is viewed as an orientation towards understanding and learning about AI in different professional contexts, including AI ethics, the ability to apply AI, and the perceived AI self-efficacy. The research questions were as follows: 1) How do HSPs evaluate the level of their AI competence? and 2) Does qualitative and quantitative work experience correlate with the perceived AI competence? The study used survey data collected in 2024 by the Ministry of Social Affairs and Health in Finland. The sample comprised 735 HSPs, approximately one-fifth of whom had supervisory duties, while approximately 60% worked primarily in customer or patient care. The respondents perceived AI as a crucial component of overall digital competence. However, they also expressed that their current level of competence, for example, in the ethical implementation of AI, was insufficient relative to the growing importance of AI technologies in everyday work. HSPs with 16–20 years of work experience exhibited the greatest AI competence deficit. In an occupational comparison, AI competence deficit was less probable among practical nurses, likely due to the well-established role of health technologies in their education in Finland. To enhance AI competence among HSPs, national and regional collaboration with educational institutions should be strengthened, incorporating both formal and informal learning opportunities.

Keywords: artificial intelligence, competence beliefs, customer work, digital competence, technological development

Introduction

Artificial intelligence (AI) is rapidly transforming the health and social care service environment, surpassing previous advancements in digitalisation [1]. Future digital solutions will be increasingly intelligent and autonomous, with the EU's AI Act (2024) facilitating the adoption of reliable AI technologies in healthcare and social services [2]. AI refers to machines that perform tasks such as reasoning,

learning and planning. Machine learning, a subset of AI, enables classification and forecasting based on input data [2–4].

Large language models, such as Chat-GPT, use deep learning and vast datasets to generate, summarise and predict text [1,3–5]. However, AI is poised to revolutionise services beyond mere patient data recording [3]. In clinical practice, AI aids in automating tasks, yet many professionals remain unaware of its full potential [6]. AI is anticipated to play a key role in neurology, cardiology, cancer care and epidemiology, supporting diagnosis, medical imaging, clinical decision-making and public health analysis [7-9].

Timely AI-related knowledge and competence are required in patient and customer work, particularly regarding applications and data collection [10]. Understanding the link between managed data and AI tools is crucial. Practitioners should be actively involved in AI-related transformations, from development to implementation, as their participation enhances job satisfaction and facilitates organisational change [11,12].

In this study, AI competence is understood as an orientation towards understanding, applying and learning about AI and AI ethics. AI ethics is generally assessed based on a system's transparency, privacy, safety and accountability. In professional settings, AI-related ethical dilemmas range from algorithmic biases in machine-driven decision-making to concerns about technological unemployment arising from the replacement of human labour with robots. Furthermore, in healthcare, AI ethics intersect with vocational ethics, which emphasise the relationships between practitioners and care recipients. Together, AI ethics and care ethics prioritise patient well-being, data privacy and patient autonomy, including the right to refuse the use of robots in their care or treatment [13].

Finland provides an interesting exemplary context for studying AI competence. The Ministry of Social and Health in Finland is promoting public wellbeing counties, private companies, educational institutions and national organisations to build ecosystems for piloting and testing AI applications. The objective of these pilot studies is to identify scalable AI solutions in health and social care [15]. As a result of this AI policy, care professionals have already gained experience with, for example, AI-supported patient pathways [16] and large language models [17].

Research on AI-based health and social services has primarily focused on topics such as health service management, predictive medicine, patient data and diagnostics and clinical decision-making [14]. However, AI competence in health and social work has not received as much attention in the research literature. In this study, we examined health and social service professionals' (HSPs') beliefs regarding AI competence. The research questions were as follows: 1) How do HSPs evaluate the level of their AI competence? and 2) Does qualitative and quantitative work experience correlate with perceived AI competence?

AI competence as a dimension of digital competence

Competence related to the digitalisation of healthcare and social work has been defined by the European Qualification Framework (EQF 4-8) [18]. The expertise areas of practical nurses (EQF 4) include the ability to use and promote health and wellbeing technologies [19]. At the higher education level (EQF 6), multidisciplinary competence and AI-related skills are emphasised in areas such as monitoring, knowledge management and information management [20]. In the eHealth competence education for doctors of medicine and dentistry (EQF 7), AI is mentioned in connection to

electronic databases and decision-making support [21,22]. The general competence requirements of the social sector (EQF 7) and the need for further education have been also defined [23].

The microcredential system represents an educational and training framework that integrates small competence sets into formal education. These smaller competence modules are identified and incorporated into different curricula as learning content, leading to formally recognised competencies within educational settings [24].

Within Finnish research, AI competence is recognised as a dimension of digital competence [19-23]. The International Medical Informatics Association first defined competencies related to biomedical and health informatics in 2010 [25] and most recently updated them in 2023 [26]. Based on thematic analysis of interviews, AI competence includes foundational AI knowledge and understanding of its social and ethical implications, AI-enhanced clinical encounters, evidence-based evaluation, workflow analysis and practice-based learning [27]. Additionally, it involves acknowledging both the capabilities and limitations of robotics and maintaining a realistic understanding of how robots can be utilised effectively in everyday work [28]. Ethical implications are particularly significant in human-centred professions. In health and social services, decision-making is morally laden, complex and sensitive, and the readiness to adopt smart machines or applications is affected by their perceived accountability, transparency, permission and privacy [1,13,29,30].

For this study, AI competence deficit (AICD) was operationalised as the disparity between the perceived importance of AI-based technologies and individuals' competence in using them. When HSPs evaluate their AI competence at work, the theory of self-efficacy becomes relevant. Self-efficacy refers to an individual's belief in their ability to succeed based on their personal competence [31]. The self-reported evaluation of competence should be understood as a subjective belief of one's competence – metacognitive self-efficacy. Self-efficacy has been identified as a robust factor in technology acceptance within professional settings [30-32], and occupational self-efficacy is strongly influenced by expertise [33]. Based on this understanding, we formulated the following hypothesis: AICD is more probable among respondents with less work experience.

Material and methods

The study used survey data collected by the Ministry of Social Affairs and Health in Finland. In 2024, HSPs across Finland were invited to participate in an electronic questionnaire distributed ex officio. Participation remained voluntary. Study invitations, along with two reminders, were forwarded to employees by their respective professional managers within the wellbeing counties. A total of 735 responses were obtained in the set timeframe of two weeks.

The questionnaire included items related to the respondents' occupational backgrounds and sociodemographic information. Subsequently, the respondents were asked to evaluate various aspects of digitalisation, assessing both the perceived importance and their personal competence in these areas.

The questionnaire included statements about utilizing AI in the respondents' professional roles to assess their AI competence beliefs. The statements were primarily adapted from an established scale introduced by Carolus et al. [34], which assesses AI literacy and AI self-efficacy (e.g., "I can keep up with the latest innovations in AI applications"). Additionally, an item from Turja et al. [35] was incorporated

to capture informal workplace training aspects of AI self-efficacy (e.g., "I'm confident in my ability to learn how to use AI in order to guide others to do the same").

The HSPs responded to seven statements—first, evaluating the perceived importance of each aspect, and second, assessing their personal competence in these areas, resulting in a total of 14 statements. The responses were recorded on a four-point Likert scale: 1 = Disagree, 2 = Somewhat disagree, 3 = Somewhat agree, 4 = Agree.

The mean of means in perceived importance was calculated as 3.23 and that in personal competence was calculated as 2.74. The within-subjects difference between perceived importance and personal competence was computed as a delta variable. These individual delta variables were then aggregated into a composite mean variable, AICD, which was used as a dependent variable in the subsequent analyses. AICD measured the discrepancy between a person's perceived importance of AI and their self-reported AI competence, with a larger gap indicating a greater competence deficit. Table 1 presents descriptive statistics on AI competence beliefs and AICD.

In the multivariate analysis, AICD was examined through explanatory variables representing qualitative and quantitative work experience. Qualitative work experience was categorised by occupation. Registered nurses comprised the largest subgroup (25%), followed by social workers and 'other healthcare workers', each representing 11% of the sample. Executives and practical nurses accounted for 8% each, while other professional groups included doctors of medicine and dentistry (7%), social services administrators (7%), head nurses (6%) and physiotherapists (5%).

Table 1. Descriptive statistics for assessed importance and competence of AI-assisted systems.

	Importance		*Competence*		*Imp-Comp*
Statement	***Mean***	***SD***	***Mean***	***SD***	***Δ (Mean)***
I can assess what advantages and disadvantages the use of an AI entails	3.51	0.69	3.10	0.85	0.43
I can use AI applications to make my everyday work easier	2.99	0.97	2.44	1.00	0.63
I can operate AI applications in my field of work	3.20	0.84	2.65	0.95	0.59
I can keep up with the latest innovations in AI applications	3.11	0.95	2.48	1.02	0.68
I can imagine possible future uses of AI	3.10	0.87	2.73	0.94	0.37
I can analyse AI-based applications for their ethical implications	3.33	0.87	2.78	0.95	0.78
I'm confident in my ability to learn how to use AI in order to guide others to do the same	3.39	0.79	3.18	0.92	0.22
Internal consistency (α)	0.87		0.90		

Quantitative work experience was measured by the number of years the respondents had worked in health and social services. The most common category was 'over 20 years' (38%), followed by 16–20 years (15%), 11–15 years (15%), 6–10 years (15%), 3–5 years (9%) and two years or less (8%).

The statistics are reported as percentages, means (M), standard deviations (SD), delta variables (Δ) and Cronbach's alphas (α). The multivariate analysis included correlation coefficients (r) and nonparametric Kruskal-Wallis tests (H). Statistical analyses were performed using SPSS (version 29).

Results

The majority of respondents were female (89%), with ages ranging from 20 to 68 years (M = 47). Approximately one-fifth (22%) of the respondents had supervisory responsibilities as part of their job descriptions. Additionally, over half (62%) were primarily engaged in direct customer or patient care and nearly the same proportion (61%) reported performing their customer or patient work digitally.

Perceived importance of and competence in AI

In a preliminary examination, the items of perceived importance of and competence in AI showed adequate variance. Individual statements of AI importance and competence were rated on a scale from 1 to 4 (Table 1). When evaluating the importance of AI competence, the respondents prioritised the ability to assess the advantages and disadvantages of AI usage (M = 3.51). The least important objective was the ability to use AI applications to make every day tasks easier (M = 2.44). Among the seven evaluations of individual competence, the highest self-reported competence corresponded to the statement 'I'm confident in my ability to learn how to use AI in order to guide others to do the same' (M = 3.18), while the lowest self-reported competence was in response to 'I can use AI applications to make my everyday work easier' (M = 2.44).

Less than one-third (29%) of the respondents perceived their AI competence as aligned with the perceived importance of utilizing and understanding AI-assisted technologies. While 12% reported having greater competence than importance, the majority (59%) exhibited AICD. The AICD scores ranged from -2.14 to 3.00 (M = 0.53; SD = 0.70). The greatest competence deficit was observed in analysing AI-based applications for their ethical implications (M = 0.78), whereas the smallest competence deficit was found in the confidence to learn AI to the extent of guiding others (M = 0.22).

Association between AICD and qualitative and quantitative work experience

To test the first AICD hypothesis, we examined whether AI competence deficit varied across different categories of work experience. A statistically significant difference was found among the experience-based groups ($H(5) = 17.45$, $p < 0.005$), but the relation was not linear. HSPs with three to five years of work experience reported the lowest AICD, whereas those with 16 to 20 years of experience exhibited the highest AICD. This is particularly noteworthy, as age correlated only marginally with AICD ($r = 0.105$, $p < 0.01$). Consequently, the hypothesis predicting a linear relation between shorter work history and higher AICD was not supported. A secondary analysis further revealed a very slight negative correlation between graduation year and AICD.

In the examination of the second hypothesis, that is, AICD variance in different occupations, AICD was significantly less probable among practical nurses (M = 0.21, SD = 0.61) compared to other occupational groups ($H(9) = 17.37$; $p < 0.05$). Conversely, the highest AICD levels were found among

physiotherapists (M = 0.21; SD = 0.61) and head nurses (M = 0.73; SD = 0.75).

Discussion

This study examined AI competence beliefs among HSPs. The findings indicated that the Finnish HSPs exhibited a strong appreciation for the role of AI-based technologies in their fields. The respondents consistently highlighted the importance of understanding AI's advantages and disadvantages, yet their self-perceived competence in AI was notably lower than what they considered necessary. The most significant competence gap emerged in the area of analysing AI-based applications for their ethical implications.

These findings align with the concerns raised by Davenport and Kalalota [1], who argued that healthcare institutions, alongside governmental and regulatory bodies, bear the responsibility for AI integration and must establish governance mechanisms to mitigate potential risks. AI-based systems have been recognised as susceptible to miscalculations, biases and compromising patients' health and treatment, as well as triggering prejudices, all of which can have negative consequences on patient profiling [29]. In addition to government-level responsibility, the staff using AI-based systems must themselves be aware of these risks, which necessitates adequate AI competence and digital literacy. Professionals must align their ethical guidelines with the responsible use of AI [13], requiring knowledge of both AI functionalities and professional ethics.

AI in healthcare technology has potential to make digitally literate HSPs' work easier in terms of more intuitive or automatic AI-based processes. However, we need to identify and support professionals with lower digital literacy. Kuek and Hakkenes [36] emphasised targeted education and training among HSPs who lack confidence in using digital tools, such as information systems and electronic health record systems. This recommendation for targeted educational interventions is as timely as ever, since information systems and other technological applications are becoming increasingly intelligent, needing specific literacy skills, such as algorithm literacy and care robot literacy [13,37].

In our hypothesis regarding the association between shorter work experience and AICD, we posited that the established relationship between occupational self-efficacy and accumulated occupational expertise [33] can also translate into work-related AI self-efficacy. Although the findings do not fully support the expectations, they provide insights into the multifaceted nature of workplace readiness for technological transformation across different generations of experience. HSPs with three to five years of work experience reported the lowest AICD levels. One interpretation is that this group has already received basic education in AI, which has partially enabled them to engage more actively in informal workplace training on AI.

Among the occupational groups, practical nurses exhibited lower AICD. This finding indicates how most of the practical nurses in Finland have used healthcare technology in patient care as part of their formal education [19,38] and have built confidence in using also new-generation technologies. As another interpretation, practical nurses can be viewed as having a relatively straightforward job description of taking care of patients and using technology routinely in their everyday work. Those with more complex roles in practice and leadership may find themselves lacking digital and AI competence due to the high education and demand of their current responsibilities. Experts may underrate a familiar domain compared to the one they

have little information about, a phenomenon known as expert bias [39,40,21].

In practice, AI has clinical, financial and operational applications, making HSP involvement in development and organisational changes crucial [24]. Nurses, for example, play a key role in assessing technological relevance [11,12]. More broadly, HSPs should be actively engaged in all stages of AI adoption [3,6,7,9,11]. The respondents viewed AI competence as a key element and future requirement in digital competence. Beyond degree-based education [18,19,20–23], continuous formal and informal AI training is needed. Flexible learning pathways, such as micro-credentials, offer professionals stackable credits to enhance their skills [24,31].

This study has several limitations related to the questionnaire design and timing, as well as the sample. First, the absence of a predefined AI definition may have introduced unintended variance in the responses. Second, for respondents with no experience in AI-based systems, the questions may have seemed overly hypothetical. Finally, the sample was relatively small and imbalanced considering the number of occupations it represented.

Ethics statement

The study was conducted in accordance with good research practice, adhering to the European Code of Conduct for Research Integrity and complying with the regulations outlined in the World Medical Association Declaration of Helsinki [41] and the European General Data Protection Regulation [42]. The data collected for this study did not include any direct identifiers that could be used to identify individual respondents. Informed consent was obtained from all participants at the beginning of the survey.

Conclusion

The HSPs' perceptions of AI-assisted health and social services reflected readiness, realism and reliance. Readiness was evident in the strong emphasis placed on AI's importance and the widespread appreciation of AI-related skills, which surpassed other digitalisation scenarios. The respondents viewed AI-assisted systems as a transformative force that is expected to enhance work processes positively. Realism emerged in the recognition that AI competence is still developing, which is a natural outcome in an era of emerging AI. Confidence in AI use was higher among those with a few years of experience but relatively new to the field. Reliance was seen in strong future-oriented competence beliefs. Few felt intimidated by the new demands of AI-assisted work. Despite its limited current use, the HSPs expressed high self-efficacy, expecting to learn AI systems well enough, even to the extent of guiding others.

Conflict of interest statement

The authors report no conflicts of interest in this work.

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