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Artificial intelligence in wellbeing services counties: management and experts' perspectives on opportunities, challenges and AI readiness

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Abstract

Artificial intelligence (AI) can be used to enhance healthcare efficiency and quality. New generative AI (GenAI) and large language models (LLM) offer novel opportunities for AI applications. This study examines management and expert perceptions of AI implementation opportunities and challenges in wellbeing services counties (WSCs), which are the responsible providers of healthcare and social welfare services in their region in Finland.

A qualitative interview study was conducted in two phases from Nov 2023 to Feb 2024. First, 28 participants were interviewed semi-structurally. Thematic analysis was used to identify potential AI use cases, main use contexts, and related benefits and challenges. Second, 16 participants (14 new persons and two already interviewed) validated the results in four group interviews and prioritised the use contexts by their potential for WSCs. The framework of Roppelt and colleagues was used to analyse the AI readiness of WSCs.

Six AI use contexts were identified and prioritised: 1. Clinical healthcare, 2. Patient interaction and self-care, 3. Support services, 4. Management, 5. Preventive healthcare, 6. Social welfare services. AI readiness should be increased by the government by supporting organisational collaboration, experience sharing and regulatory interpretation. Healthcare organisations need to improve AI competence and skills at all levels. Regulation and WSC culture not supporting experimentation were identified as main challenges for broader AI implementation.

AI particularly GenAI, is seen as a promising technology to address workload, financial, and service demand challenges in WSCs. Challenges can be mitigated through focused collaboration and actions within and between stakeholder organisations. AI implementation research in healthcare should consider the rapid development of AI, including increasingly human-like behaviour and integration into physical robots.

Keywords: artificial intelligence, wellbeing services counties, digitalization, healthcare, implementation, interview study

Introduction

In mainland Finland, the responsibility for organising health, social and rescue services lies with 21 wellbeing services counties (WSCs) and the city of Helsinki [1,2]. The self-governing WSCs were established in January 2023 and are currently undergoing a significant transformation to digitalise their services and data management, in accordance with the Ministry of Social Affairs and Health's strategy for the years 2023-2035 [3].

Also in recent years, AI technology has reached the interest of the publics due to the open, easy-to-use and surprisingly well functioning chat robots such as ChatGPT [4,5]. The chat robots serve as natural-language interfaces to Large Language Models (LLM), that are built with advanced AI techniques [6,7] and can produce new content-wise textual material in seemingly human-level quality, for instance code [4] or poems [8]. AI generating new content based on training data is called Generative AI (GenAI). Free and publicly available GenAI and AI-powered virtual conversational agents [5] could democratise use of AI in healthcare [9].

AI in healthcare is not new. Machine learning (ML), a central sub-technology of AI, has been applied in healthcare for decades, mostly in predictive analytics [10,11]. Deep learning methods and convolutional neural networks have enabled advanced analysis of medical images [10]. In this kind of narrow tasks, AI can perform better than a medical expert [11].

"Classical" ML-based AI handles structured, tabular-form data, whilst modern GenAI is able to process unstructured data: narrative free-form texts, sounds, images, and videos [11]. For instance, GenAI can find and process clinical variables from electronic health records into a structured form [12]. LLMs have shown from moderate to good performance in medical query tasks, assessing medical skills, assisting diagnosis and interpreting and simplifying medical language [4]. LLMs trained on vast scientific literature could potentially forecast novel results in neuroscience better than human experts [13]. Currently LLMs still suffer from many weaknesses, such as biases in training data, generation of harmful content and privacy concerns [5]. One of the main deficiencies is hallucination, i.e. confabulating factually inaccurate content [5,14], which seriously restricts the clinical utility of GenAI [4]. Techniques such as Retrieval-Augmented Generation (RAG) have been developed to mitigate hallucination [5].

Outside clinical practice, both classical and GenAI could be applied in public health, biomedical research and health administration [15]. More specific application areas are for instance medical imaging and diagnostics, virtual patient care, medical research and drug discovery, patient engagement and compliance, rehabilitation, personalised medicine, virtual assistants, identification and managing public health risks and other administrative tasks [10,16]. Also robots in surgery and rehabilitation can be considered as AI implementations [10].

The aim of our study was to understand the role and benefits of AI in Finnish WSCs. AI is mentioned in more than half of the WSCs' digitalisation strategies [17], but utilisation of AI is still limited [2,18]. In the study, we applied a theoretical framework of Roppelt and colleagues [19] to examine AI readiness in the WSCs. Research has only weakly used implementation literature on AI adoption in healthcare: studies have focused on the design of technology and interaction [20] or clinical applications [19]. GenAI clearly extends AI opportunities beyond clinical use in large-scale, multi-service public organisations such as WSCs. In addition, AI implementation should be studied at both user, organisational and societal level [19,20].

Theoretical approach to AI implementation

Roppelt and colleagues [19] have developed a framework addressing implementation of AI in healthcare organisations. The framework includes five antecedents to be investigated and developed to advance large-scale implementation of AI.

Of the three external antecedents, the *macro-economic readiness* requires advanced IT infrastructure and supportive communications, developed by the government. The *technological readiness* is driven by AI providers, which should demonstrate multi-faceted value propositions for their AI solutions, overcome the algorithmic challenges and develop evidence-based applications. The *regulatory readiness*, managed by the government and regulatory bodies, can be achieved by developing the regulations and their clarity, providing guidelines and showing political support.

Of the internal antecedents, the *organisational readiness* is increased by preparations prior to the AI adoption: a healthcare organisation needs a top-down organisational strategy for AI, a supportive organisational culture with change ambassadors, consideration of tasks suitable to AI, and an adequate IT setup able to incorporate external software, with updated hardware and robust data privacy and security measures. The *user readiness* refers to the level AI awareness, beliefs, competences and skills of both professional users and citizens.

We retrospectively applied the framework to assess the AI readiness of WSCs and identified facilitating actions for AI implementation.

Aim of the study and research questions

The aim of this descriptive interview study was to increase understanding of the role, implementation and adoption of AI in WSCs, the responsible organisers of social and health care in Finland. The study explored the perspectives of management and experts. The research questions were:

> How is AI and its usage perceived in the context of wellbeing services counties?
>
> What are the main benefits and challenges of implementing AI in wellbeing services counties?
>
> What insight does the data provide regarding the AI readiness of wellbeing services counties?

Our focus on WSCs excludes some application areas of AI from the study, namely medicine development, medical research, and healthcare and medical education. Rescue operations were excluded due their focus on emergency situations. Robotics was excluded as a technology requiring physical implementation unlike mere AI.

Data and method

The empirical study was part of a project of DigiFinland to map stakeholders' views on AI in WSCs. The study was a two-phase qualitative inquiry with management and expert participants (Table 1). The participants were selected by purposive sampling due to their expertise on the theme (thus, expert sampling) [21,22]. The project steering group deliberated and suggested interviewees in weekly meetings to gather a variety of perspectives for the study. In the later group interviews, the WSC participants also proposed relevant persons themselves. Altogether 45 participants were invited by email, and 42 accepted the invitation. Two of them did not provide consent to use their interview data in this study, thus n=40. In this group, 16 participants were from four different WSCs.

The method is illustrated in Figure 1. First, 26 participants were interviewed either individually, or in four cases, in groups of 2-3 persons for collecting data for initial findings. In the second phase, 16 participants (14 new and two already interviewed ones) participated in four group interviews with 2-6 persons each to validate and prioritise the findings from the first phase.

Table 1. The professional role of the participants.

Participants	Phase 1. Interviews	Phase 2. Validation	Total
IT managers from WSCs	2	9	11
IT managers from private sector	5		5
Clinical managers	4	1	5
Digital health service managers	3	1	4
IT experts	4	1	5
Researchers	3		3
Other experts*	3	4	7
Number of participants	26**	16	40**

* Clinical, data protection, societal development, governance, regulation, project coordination

** Two participants did not consent to the use of their interview data

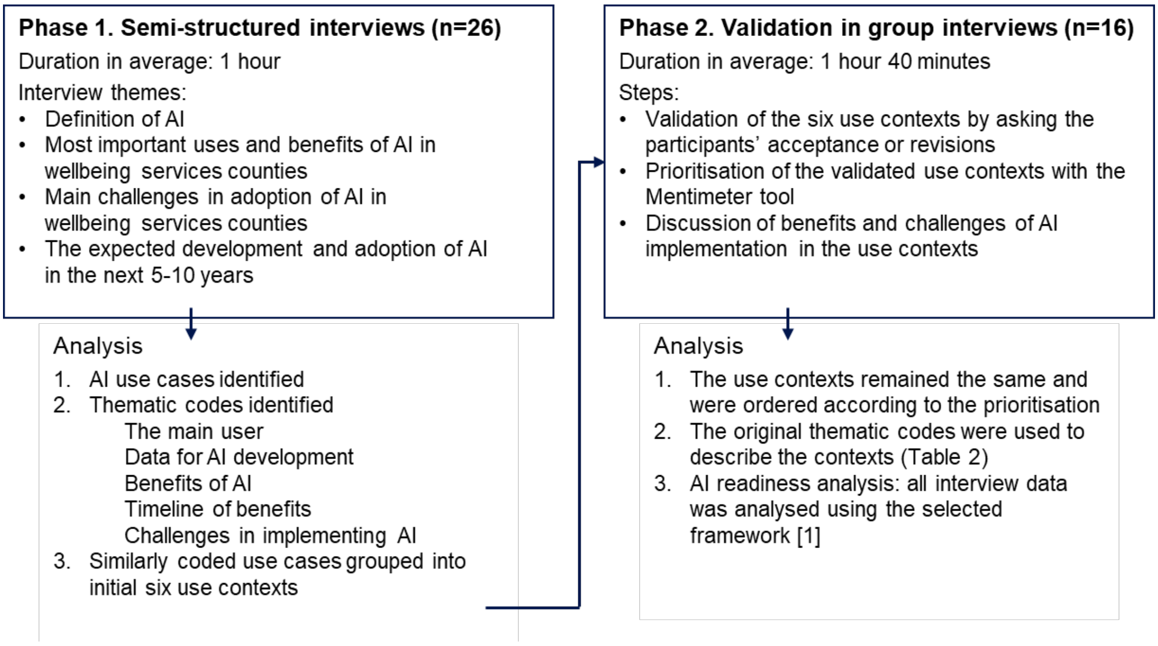

Figure 1. The data collection and analysis in two phases.

All interviews were carried out during 11/2023-2/2024 in Microsoft Teams by either one or two of the authors, who also took written notes on computer. In some interviews, an assistant took complementary notes for the interviewing author. The interviews were not recorded or transcribed. In total, the study material consists of approximately 100 A4 pages of interview notes data. In addition, one of the individual interviews was transcribed via the built-in live transcription feature in the Teams software.

The interview data was originally collected for purposes of DigiFinland, and used in this study as a secondary data with the permission of the organisation. Consent for the anonymous use of the interview data for this article was requested from the participants retrospectively via email.

The data was thematically analysed [23]. The interview data was first read to identify AI use cases and to code thematically meaningful characteristics of them (Figure 1). The use cases were organised by the identified thematic codes (e.g., the main user, benefits and challenges related to a particular use case). The use cases were then grouped into six categories, making six use contexts of AI in WSCs. Second, the use contexts were validated in the group interviews by discussing each context and related use cases. The contexts did not significantly change in this process. The participants individually prioritised the use contexts by their potential by using the Mentimeter tool's live polling feature [24], which supports visual ordering of items, scores the items according to their ranking and combines the scores to the group's joint ranking list. The prioritisation was discussed in the groups for further validation. Finally, all interview data was examined using the framework of Roppelt and colleagues [19] to identify and categorise mentions related to the five AI readiness factors, to provide insight about the AI readiness of WSCs.

In the original analysis of the data, we identified more than 50 use cases of both traditional and genAI in the six use contexts, already published in Finnish [25]. Here we analyse the data in more detail to provide deeper insight on the role of AI in WSCs.

Results

Use contexts of AI in WSCs

The AI use cases differed according to the application main user (clinical/healthcare professional, patient, management, personnel, social care professional), characteristics of data needed for AI, application benefits, timeline of benefits (short-term–long-term) and implementation challenges. These themes were used to group the use cases into six use contexts (Figure 2, Table 2). The prioritisation of the use contexts reflects the perceived potential of AI in each context as assessed by the participants. In the group interviews, the participants justified the prioritisation of the use contexts with several factors: most important was the potential of AI as saving the professional's time, then the benefit of AI in saving costs or resources, health risks due to use of AI, regulation that needs to be considered when developing or using AI, the expected timeline of realising the benefits, and data availability and accessibility in that particular use context.

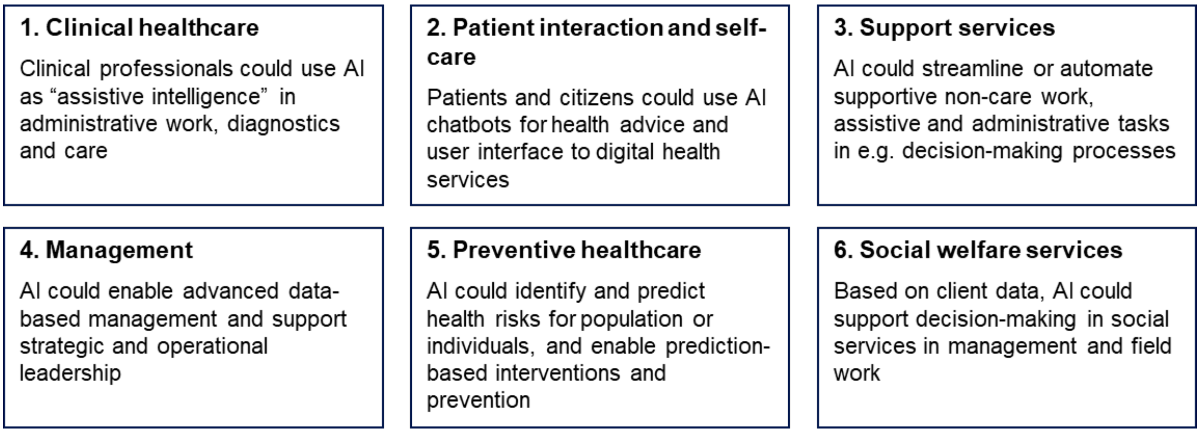

Figure 2. The six use context of AI in WSCs.

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Table 2. AI use contexts in WSCs in their prioritised order.

Theme	1. Clinical healthcare	2. Patient interaction and self-care	3. Support services	4. Management	5. Preventive healthcare	6. Social welfare services
Main user	Clinical worker: medical physician, nurse, healthcare professional	Citizen, patient, social welfare service client	Personnel from finances, IT services, human resources, logistics etc. (non-care work)	WSC chief executive, service area manager	Decision-maker in medical and healthcare services	Social care manager or professional, practical nurse
Characteristics of data	Clinical and health data + general health and medical information Well-developed health data sets exist but not easily available	Personal health and wellbeing data + general health and medical information No general data sets exist nor are available	Service-related data (no health-related personal data): financial data, information system log data, work shift data, resource use data etc. Data sets available from information systems	Data from many sources, aggregated health data for secondary use Data sets available	Clinical data, data from health and social services, wellbeing data + general health, medical and social welfare information Well-developed data sets, not easily available	Narrative data + general health and social welfare information Data sets less developed, not easily available
Main benefits	Liberating care professionals from non-care/non-medical work and "paperwork"; saving resources for actual care work, increased work satisfaction Improved interaction with the patient Improved diagnostics, treatment planning and follow-up with less resources	Self-service and self-care save personnel resources to critical care work Increased availability of services for the patient Assistance to find information, right service and professional; better service experience Better engagement of patient to care	Saving resources in administrative "paperwork" Automation in reporting Facilitating and lowering costs of translation	More efficient resource use, management and coordination Financial sustainability	Saving resources and creating health benefit in the long-term (?) Optimised support for patient's lifestyle change Developing focused interventions to specific areas, populations or individuals	Liberating care professionals from "paperwork"; saving resources for actual care work Improved interaction with the service client Support for decision-making based on large, complex narrative information
Benefits time span	Short-term: non-medical applications, low-risk applications Long-term: medical applications such as assistance in diagnostics	Short-term: non-medical applications, low-risk applications Long-term: medical applications such as assistance in self-diagnosis, self-care	Short-term: AI assistance in current work	Middle-term: advanced knowledge-based management	Long-term	Middle-term, long-term: analysis of narrative texts, support for decision-making

Theme	1. Clinical healthcare	2. Patient interaction and self-care	3. Support services	4. Management	5. Preventive healthcare	6. Social welfare services
Main challenges of implementation	Regulation: Medical Device Regulation, AI Act, data access regulation (e.g., GDPR) Risk of malpractice Reliability and explainability of genAI	Lack of user skills, digital devices and digital literacy Resistance to change Users need easy-to-use interfaces	Weaknesses in service management, weak capability to use AI	Underdeveloped data-based management	Evidencing the benefits requires several years, even decades (e.g., preventive interventions for dementia) Data is fragmented and regulation hinders integration of multiple data sources (e.g., health data and social data; data from two WSCs) for meaningful uses	Weaker culture of using AI and knowledge-based management, less data intensive work compared to healthcare Database not well developed (Early) interventions difficult Data is fragmented and regulation hinders integration of multiple data sources

1. Clinical healthcare

This use context was expected to be the most important in a longer term. Clinical professionals need AI to liberate them from routine and administrative tasks to face the patient and carry out the actual diagnosis and care work. GenAI is expected to automate medical notes, draft medical certificates, cross-check medicines and support diagnostics in many ways. The ultimate value and challenge in this use context is that how to apply AI to facilitate decision-making in care without crossing the line of high-risk medical AI and raising difficult ethical questions. Keeping the health professional as responsible and accountable and allocating AI an assistive role was seen as a solution. Regulation and fear of confronting regulation were seen major hindering factors in developing and experimenting new AI uses.

2. Patient interaction and self-care

The potential of this use context was in automating and supporting the patient-service interaction to decrease need of care resources. AI could provide automated patient follow-up, health advice and customer assistance, and interpret self-measurements of health. In a long term, therapy chatbots and personal AI doctors enabled by genAI were seen promising, but their development was challenged by regulation of high-risk medical AI and automated decision-making as well as user acceptance.

3. Support services

This use context was perceived to have the most feasible uses of AI in a short term, as it consists of general knowledge work carried out on generic use software without medical devices or ethical problems. Solutions are already on the market and partly in use, e.g. in IT services. AI could assist in preparing decisions and impact assessments, and produce guidelines and instructions for various tasks. The value of use cases for employees was saving time from searching, summarising and preparing information tasks. The challenge was that the long-term impact could be also negative due to AI costs.

4. Management

WSC managers could benefit from AI predicting service needs, resource use and costs. AI could help to better understand the impact of services, and enable advanced monitoring of care, service use and processes. AI analysing a wide information base could provide the management deeper understanding and insight of the WSC's situation and development. The challenge in this use context was seen as the low level of knowledge-based management skills in WSCs. Existing practices were seen to be so robust that AI would be underutilised. For instance, smart workshift planning tends to be weakly utilised since managers of care rather maintain the habit of autonomous planning.

5. Preventive healthcare

The impact of using AI to predict health risks and plan focused or personalised interventions for individuals or populations was expected to be significant. Nevertheless, this use context had several major challenges related to data that is needed to develop useful predictive models: it is difficult to collect the data due to regulation and unmotivated WSCs (register-holders). It is unclear when a predictive AI is classified as a medical device. There is a lack of skills in utilising predictive information, as well as a lack of relevant preventive services. Ethical questions also need to be considered. Impact of prevention could be high at the individual level, but feasibility is low due to data restrictions, regulation and possible need of consent. At the population level, feasibility of predictive AI was seen to be high but the impact of preventive actions lower. The main challenge, however, was that the development of predictive AI models is underfunded since the positive impact of prevention would be far in the future and difficult to prove.

6. Social welfare services

This use context was seen as having a high potential for AI but low capability to adopt it. Compared to healthcare, the database in social services is narrow considering classical ML algorithms (requiring structured data), but LLMs able to process masses of text data provide new possibilities for social services. AI could identify customer profiles and predict the impact of service. AI enabling early identification of social risks and early social support would have a major impact, but regulation was not seen to support this. Ethical concerns were seen difficult: is it right to pick up persons and offer them services preventing e.g. alcoholism or loneliness if the person has not requested for help? In services for older adults, remote monitoring of the person at home and AI-assisted risk prevention was recognised as a useful case.

AI readiness

All mentions of AI readiness in the interview data were categorised according to the five AI readiness factors [19] and abstracted into findings, ensuring that each finding had distinct content. The findings were further categorised into development needs, challenges and other observations that relate to WSCs readiness to implement AI (Table 3).

Table 3. AI readiness of WSCs.

AI readiness dimension	Development needs	Challenges	Other observations
Macro-economic readiness	IT infrastructure: easier access to big computation Collaboration: support for national collaboration, open communication, sharing best practises, sharing risk and impact assessment and cost-analyses between various actors; for sound impact research; for a neutral and safe social setting to ponder and invent solutions for healthcare and WSCs Data: national support for sharing raw data and integrating data from many sources (from different public services); for methods/policies to ensure fairness of data and undiscriminating AI models Funding: funding for relevant, large-scale solutions; public bidding needs to be developed for innovative solutions Support public and private actors' partnerships		
Technological readiness	Evidence of the impact of AI solutions Tools monitoring the quality of AI response, technical safety nets for use;		ML tools are advanced and in use;

	platforms enabling scalability of useful AI solutions		GenAI innovations are being developed
Regulatory readiness	Clarification of at least national regulation	Excessive regulation load is perceived as a major challenge by developers and deployers: regulation slows down AI experimenting, learning and utilisation of data, and so also indirectly sustains fears and misconceptions about AI Strict national and varyingly strict local interpretations make both international and national collaboration difficult; local interpretations lead to overly cautious behaviour	EU regulation (AI Act, MDR) perceived more positively than national regulation (secondary data use in particular)
Organisational readiness	Autonomous collaboration: WSCs could self-organise co-operation to develop and invest AI solutions without direct national support; pioneer organisations can experiment and share results (for incentives?) Internal collaboration: a WSC needs an owner-promoter team leading AI; improved collaboration between IT and service management Competence: Increasing AI skills and competence at all levels of organisations and in all organisations Change ambassadors: single key persons can have a major impact in organisational change	Experimenting culture: WSCs suffer from fear of mistakes, the precautionary principle takes too much effort and time; "they first look at regulation" whilst learning by doing would be necessary also to motivate legislation changes Business from data: WSCs show resistance to companies looking for profit from (health) data owned by the WSCs, which slows down development	Digital culture: WSCs differ in their attitudes, applications in use, and interpretation of regulation
User readiness	End users need digital skills to benefit from AI solutions and to understand their limits (e.g., bias) Professional users need training of AI and cybersecurity; they should also learn to identify where manual work can be automatised		

The participants suggested clear development needs to enhance AI readiness of WSCs. The government should support national-level collaboration for increased data use, sharing knowledge and commercial purposes, and provide funding for AI development. AI providers should show evidence that applications of AI and GenAI in particular are useful, reliable, safe and scalable, and have a positive impact. Regulatory bodies should clarify the national regulation to facilitate implementation of AI. WSCs could self-organise external collaboration with relevant actors, improve internal collaboration and build internal teams to lead AI implementation. All health organisations should increase their AI skills and competence. The user readiness could be increased by developing their AI skills, and increasing the professional users' capability to advance automation in their work tasks.

Two major issues seem to hinder implementation of AI: regulation and WSC culture. The complex regulatory network and the varying local interpretations slow down collaboration, development and implementation of AI. By making experimentation difficult, regulation also indirectly sustains fears and misconceptions about AI, which in turn can increase distrusts towards development and experimentation. Furthermore, WSCs may suffer from culture of non-experimentation that over-emphasises cautiousness and avoidance of regulatory mistakes: "In a way, they first look at what the regulation says, rather than implementing a solution and then trying to fit it into the regulation." (IT expert, quote with permission). Another challenge is that WSCs may not widely accept the idea that private sector would use their health data e.g. to train AI models to make business and profit, even when the AI solution would benefit the WSC as well. WSCs nevertheless differ in their digital culture: some WSCs are more open and capable to implement AI, experiment with it, and interpret regulation accordingly.

Discussion

WSCs struggle with the ageing population, increasing service needs, low availability of care professionals and related difficult access to services [2]. WSCs can benefit from AI in social and healthcare services but also in management, support services and preventive healthcare. The use contexts (Figure 2) elaborate earlier frameworks of AI application areas in healthcare [10,15,16] for the purposes of WSCs. Specific AI use cases for each context have been published in [25]. The readiness analysis provided in this study, following [19], points out actions for various stakeholders to promote wide-scale AI implementation in the WSCs. For instance, WSCs can internally organise AI lead teams and increase AI competence. The government has already taken further actions by establishing an AI ecosystem and funding ten experimental AI projects in WSCs [26,27].

WSCs may be in an unequal position to implement AI and realise its potential. WSCs vary in their digital culture and resources for experimentation, and "pioneer" WSCs such as the ones participating in this study showed willingness to lead experimenting of AI and own the competence resulting in this process. They could independently collaborate with relevant actors. Other WSCs may suffer from weak capability to learn and implement AI. If this is related to other region-dependent challenges such as a high share of older adults and difficulties to hire care professionals [2], those WSCs in biggest need for AI to ensure the quality and availability of services would not be able to take the technology into use. The government has a key role in ensuring that those WSCs can benefit from AI as well. Future research should investigate how the less AI-ready WSCs could keep up with the development; for instance, could WSCs share their data and engage in bolder collaboration with AI providers for the benefit of the WSC.

Complex regulation was perceived as a major obstacle in developing and applying AI in social and healthcare services. The participants were very aware of risks of AI concerning health and safety, and tended to perceive risks as an avoidable issue. However, without experimenting is difficult to gain experience and knowledge, and without the latter it is difficult for the WSCs to justify requests to develop certain AI applications or to change legislation. The government and regulatory bodies need to collaborate with WSCs and AI providers to show or create safe regulatory paths to proceed. Concrete steps have been taken, for instance, by clarifying regulation of some GenAI use cases [28] and renewing the Act on the Secondary Use of Health and Social Data [29].

The framework of AI adoption in healthcare organisations [19] was found to be a useful tool for investigating AI readiness of WSCs. In the future, AI is likely to develop to interact more like humans and collaborate in human decision-making [20], finally making decisions autonomously [30]. Also, implementing GenAI in a physical robot body will allow AI to capture and mimic the physical, spatial and social aspects of human activity [20,31]. Future frameworks should better cover these technology trends and guide organisations to envision novel, more far-reaching uses of AI than those which are currently normative.

Strengths and limitations of the study

The main contribution of the study is that it reveals new and topical knowledge about how WSCs perceive AI. The study validity can be considered quite high due to both 40 participants representing various expertise and management as well as the two-phase study procedure. The validity is limited, however, in terms of time: the study was carried out when GenAI was in a 'hype' phase [32], thus the participants' expectations of AI might have been elevated by media or marketing discourse. Similar observations have been made with care robots [33,34]. This effect highlights the importance of experimentation to create understanding of AI in real-world use.

As a major limitation, the study lacks the perspectives of service users (citizens), care professionals working in the field (excluding two medical physicians) and social welfare professionals. The impact of AI on them could be significant. End-user acceptance is necessary for a new technology to be fully adopted and to realise its benefits [35]. For instance, developing AI-assisted social welfare services should be co-developed with customers to ensure value co-creation: that the automated services enhance people's well-being rather than diminish it [36].

Conclusions

AI is perceived as having a high potential to solve excessive workload of care professionals and financial challenges of WSCs. The classification of AI use contexts helps technology developers, decision-makers, policymakers and end-users to comprehend various usages, benefits and challenges of AI in WSCs. To increase the readiness for wide-scale AI implementation in healthcare and social welfare services, the government and AI providers should pave the way for WSCs with support for collaboration and with safe-to-use AI solutions of demonstrated value.

Conflict of interest declaration

Two of the authors collected the original data as contract-based work for DigiFinland. The third author is an employee in the DigiFinland.

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