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Digital and AI skills in health occupations: What do we know about new demand?

Fabio Manca and Diego Eslava

This paper explores the impact of digital technologies and artificial intelligence (AI) on health occupations across OECD countries, focusing on how these innovations can support health workers amid rising demand for healthcare services. The study provides three key empirical contributions. First, it analyses nearly 55.5 million online job postings (OJPs) from Canada, the United Kingdom and the United States, tracking the demand for digital and AI skills in health-related occupations between 2018 and 2023. Second, it identifies specific digital and AI skill requirements for various health roles, revealing emerging priorities such as Health Information Management, Telehealth, and Cybersecurity. Third, it assesses the potential effects of Generative AI (GenAI) and Advanced Robotics (AR) on health occupations, categorising roles based on their susceptibility to automation or augmentation. Results show that while some occupations face automation risks, most roles stand to benefit from productivity-enhancing technologies. The findings highlight the importance of targeted reskilling policies and continuous training to maximise the benefits of AI integration in healthcare, ensuring that technological advancements complement rather than displace health professionals.

Keywords: Artificial intelligence (AI), Skills, Health.

JEL CODES: I18, J24, O33.

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Executive summary

As OECD health systems grapple with workforce shortages and rising demand for health services due to population ageing and the growing prevalence of chronic diseases, the integration of digital technologies and artificial intelligence (AI) holds promise in supporting health workers in their workflow, enhancing productivity. This technological transformation is poised to significantly transform the roles and responsibilities of health workers across OECD countries.

Against this backdrop, this paper makes three different empirical contributions. First, it tracks the recent evolution of the demand for digital and AI skills within health-related occupations. This analysis is based on data collected from online job postings (OJPs or vacancies) that explicitly mention digital or AI skills as requirements for hiring candidates in health occupations. Second, the paper examines a set of health occupations to identify their specific digital and AI skill requirements, offering a detailed view of how the digital transformation is currently reshaping various roles within health and their digital and AI skill demands. Third, amid the rapid development of Generative AI (GenAI), the paper estimates the potential impact of this specific technology as well as of advanced robotics (AR) on health occupations. The analysis provides an assessment of how health workers could be affected by both augmentation and potential substitution due to the adoption of GenAI and AR in the workplace, thereby highlighting those areas that are most susceptible to change due to these technological advancements.

When looking at trends, the analysis of OJPs reveals an increasing demand for digital skills in health occupations across Canada, the United Kingdom and the United States. Data on nearly 55.5 million OJPs show that digital-related job postings (i.e. new OJPs where at least two digital skills are mentioned by employers in the job description) account for 2-6% of frontline health occupation vacancies and 6-13% of other health sector jobs (i.e. vacancies advertised for positions in the health sector but that do not involve direct patient care[1]) in the period between 2018 and 2023.

In particular, the analysis shows, in Canada, increasing demand for skills in Health Information Management, Data Analysis, and Telehealth, along with emerging areas like Simulation/IT Automation and Clinical Informatics. In the United Kingdom, data show increasing demand for Cybersecurity, Data Analysis, and Internet of Things (IoT) skills, reflecting priorities in data protection, advanced patient monitoring, and telehealth services. In the United States, frequent demand for Health Information Management and Electronic Health Records (EHR) expertise is complemented by rising interest in Web Design, Development, and Video Conferencing, emphasising the sector's shift toward digital health services and remote care solutions.

This study also specifically assesses the demand for broad AI-related skills in health professions. The analysis shows that the demand for health professionals with AI-related skills remains a small percentage of total new job postings in health professions, ranging from 0.2% to 0.3% of total demand across the three countries in 2023. However, a notable increase is observed in AI-related vacancies in non-clinical roles within the health sector, particularly in Canada and the United States, but still only account for 0.5% to 0.6% of OJPs. This suggests AI integration may be still nascent in direct patient care but growing in areas like health management, administration, and research.

The role played by AI, however, can go unnoticed in the analysis of job postings as this new technology can affect the skill demands of existing roles rather than directly creating new job openings. So, while skills necessary to interact and use AI are not always explicitly listed in job postings since off-the-shelf applications or generative AI tools can be adopted without having to rely on AI skills, the adoption of AI system is becoming increasingly integral to many health roles, from radiologists using AI-powered diagnostic tools to nurses employing AI systems for patient monitoring. This integration reflects the evolving nature of health work, where AI and Advanced Robotics are likely to enhance or even automate workers' efforts in existing tasks. This study digs deeper into these dynamics and examines the potential for Generative AI (GenAI)[2] and Advanced Robotics (AR) in the health sector as these can represent significant enhancing productivity tools to address labour shortages by complementing workers in both cognitive and physical tasks.

The analysis categorises health occupations into four groups based on their susceptibility to automation by these two technologies: Low Risk of Automation, Potential Augmentation, Potential Automation, and High Risk of Automation. Occupations at low risk are characterised by tasks mainly involving complex human interactions and decision-making, while those at high risk involve a large share of routine, automatable tasks (either physical, cognitive or both). Occupations where augmentation is possible could see efficiency gains in a fraction of tasks through automation, while other responsibilities remain difficult to automate. Potential automation instead, refers to occupations where GenAI and/or AR can replace a majority of tasks, potentially transforming the nature of the occupation at hand, however, some tasks still require human expertise.

Results in this work, based on information from the United States, show that occupations with potential for augmentation, such as Registered Nurses and Physician Assistants but also Family medicine physicians, can benefit significantly from digital technologies that enhance human capabilities. For these roles, continuous training in advanced medical technologies, including EHR systems and telemedicine, is essential to maximise the benefits of technological integration. Other occupations like Orderlies and Medical Transcriptionists,[3] face significant automation threats in the near future due to new developments that integrate GenAI into intelligent robots and automated systems. Policy measures should focus on reskilling these workers and providing career mobility to minimise displacement.

Following these results, this study further assesses the proportion of health employment in the United States that would be susceptible to augmentation or automation. The analysis indicates significant variation in automation potential across health roles, with 32% of employment classified under potential augmentation. Approximately 4.3% of roles, such as Pharmacy Technicians, are, instead, identified as potentially automatable. The high automation risk category, comprising roles like Orderlies and Medical Transcriptionists, constitutes around 0.6% of the health workforce. The results highlight how the integration of GenAI and Advanced Robots in health is likely to reshape employment patterns but that most of the impact may be channelled through a positive augmentation of the capabilities of existing workers. This is to say that, while some roles, particularly those involving routine tasks, may face displacement, GenAI and AR technologies also offer significant opportunities for job augmentation and the creation of new roles.

While some degree of automation has the potential to alleviate some labour shortages by enable health professionals to focus more on patient care rather than on routine tasks – thereby improving outcomes and job satisfaction – more empirical work is needed to understand the full impact of GenAI and robotics integration in healthcare, particularly in terms of how these technologies will reshape specific roles, alter skill requirements, and influence the division of tasks between automated systems and human professionals. This paper represents an initial step in mapping the specific skill sets required in healthcare by leveraging big data and online job postings to monitor how GenAI and robotics are reshaping roles across the sector.

1 Introduction

The health sector, as virtually all other sectors in the economy, is undergoing a profound transformation driven by rapid advancements in digital technologies and artificial intelligence (AI). This transformation is reshaping the landscape of health delivery, creating new opportunities but, at the same time, challenges for the health workforce. The OECD Health Ministerial Statement (OECD Health Ministerial Meeting, 2017[1]) recommends enhancing health systems by promoting efficiency, embracing technological innovations, focusing on patient-centred care, and fostering international collaboration, while also implementing robust health data governance frameworks to balance data utility with privacy protection.

The integration of digital skills and AI into health represents a fundamental shift in how services are delivered, managed, and experienced by patients and providers alike. Understanding and addressing the implications of these rapid changes is, therefore, crucial for several reasons.

First, the demand for health services is increasing globally due to ageing populations, rising prevalence of chronic diseases, and heightened patient expectations for quality care. These pressures require health systems to improve accessibility, efficiency and effectiveness. Digital technologies and AI offer potential solutions to these challenges by enhancing diagnostic accuracy, personalising treatment plans, streamlining administrative processes, and enabling remote patient monitoring and telemedicine.

Second, the health workforce is a critical component of health systems. Ensuring that health professionals possess the necessary digital and AI skills is essential for the successful adoption and implementation of these technologies. The transition to a digitally empowered health workforce requires comprehensive training and continuous professional development to equip health workers with the skills needed to leverage these technologies effectively (see for instance McKinsey (2024[2])).

Third, the use of AI and digital technologies in health has significant implications for patient safety, data security, and ethical standards. AI systems, for example, must be designed to ensure accuracy, transparency, and accountability.[4] Health professionals must be able to critically assess and interpret AI-generated recommendations and data to make informed clinical decisions. Additionally, the ethical use of patient data in AI applications necessitates robust data governance frameworks and adherence to privacy regulations (see Figure 1 in OECD (2025[3]) on all relevant OECD recommendations on data governance).

1.1. Recent literature and evidence on the use of digital technologies and AI in the health sector

Recent literature provides compelling evidence of the transformative impact of digital technologies and AI in health. A report by the US National Academy of Medicine (Matheny et al., 2022[4]) highlights how AI can enhance clinical decision-making, reduce diagnostic errors, and improve patient outcomes by analysing large datasets to identify patterns that may not be evident to human clinicians (Matheny et al., 2022[4]). This study emphasises that AI can assist in areas such as imaging, pathology, genomics, and personalised medicine, leading to more accurate diagnoses and tailored treatment plans.

A recent study also explored the potential of digital health tools to improve health services delivery and health systems performance (Borges do Nascimento et al., 2023[5]). The report outlines several case studies where digital technologies have been successfully adopted to enhance healthcare access and quality. For instance, mobile health (mHealth) applications have been used to provide remote consultations, patient education, and disease management support, particularly in low-resource settings (Borges do Nascimento et al., 2023[5]).

A recent article published in The Lancet Digital Health (Lee and Topol, 2024[6]) discusses the role of AI in clinical settings highlighting the potential benefits of AI in enhancing clinical decision-making, auditing AI models, exploring treatment outcomes, and fostering innovative research. The article discusses how AI can address data gaps, support hypothesis generation, and provide prognostic insights. While acknowledging the challenges related to data quality, generalizability, and ethical concerns, the overall conclusions of the article is supportive of the transformative potential of AI in medicine.

Beyond the benefits of integrating AI into health, studies have explored key stakeholders' views regarding the challenges of this integration. Almyranti et al. (2024[7]) conducted a global survey to assess the perspectives of medical associations on AI in health. Medical associations recognised AI's potential to boost productivity and alleviate workforce shortages, but also acknowledged that its value relies on trust, ethics, skills and infrastructure. Stronger communication, education and dedicated AI-governance units are pointed out as key elements for boosting AI in the sector.

The integration of electronic health records (EHRs) and health information exchanges (HIEs) is another area where digital technologies are making a significant impact. A study published in the Journal of the American Medical Informatics Association (JAMIA) examines the benefits of EHRs in improving care co-ordination, reducing medication errors, and facilitating evidence-based practice (Vest and Gamm, 2010[8]). The study highlights that while EHRs have improved data accessibility and continuity of care, challenges such as interoperability and user interface design need to be addressed to maximise their potential.

The COVID-19 pandemic has accelerated the adoption of digital health technologies, demonstrating their critical role in managing and responding to public health crises. Telemedicine, in particular, has seen a dramatic increase in use, enabling health providers to deliver care remotely and safely (see (OECD, 2023[9]) and Koonin et al. (2020[10])). This shift has highlighted the importance of digital skills among health workers, as well as the need for robust digital infrastructure and policies to support telehealth services. More examples of how digital technologies and AI are already permeating the health sector can be found in Box 1 and in OECD (2025[3]).

Box 1. Examples of how digital technologies and AI are already permeating the health labour market

Digital technologies are transforming healthcare by altering tasks and workflows across various health professions. In radiology, AI and machine learning tools, like Merative (previously IBM Watson Health) and Aidoc, assist in diagnosing by analysing medical images such as X-rays and MRIs. These tools highlight potential issues, improving diagnostic accuracy and efficiency. AI's ability to serve as a "second opinion" reduces errors and allows radiologists to focus on complex cases, enhancing productivity. However, challenges exist, including the need for trust in AI tools, rigorous data privacy practices, and ensuring AI reliability across different settings (see for instance Alon-Barkat and Busuioc, (2022[11]) and Horowitz (2023[12])).

Electronic Health Records (EHRs) from providers like Epic and Cerner streamline patient data management. EHRs enable real-time access to patient histories, lab results, and medications, leading to more accurate documentation, reduced paperwork, and improved communication among healthcare providers. This integration allows, for instance, nurses to dedicate more time to patient care while enhancing medication management. Nonetheless, EHR systems can be complex, increasing cognitive load, and require substantial training, which can be costly and time-intensive.

Pharmacy operations have similarly benefited from digital advancements, with automated dispensing systems and pharmacy management software like Pyxis and Omnicell reducing manual errors and expediting prescription fulfilment. Automation in pharmacies increases accuracy and speed, enabling pharmacists to handle higher prescription volumes safely. These systems also provide alerts for potential drug interactions, enhancing patient safety. However, implementing automated systems involves high initial costs, ongoing maintenance, and substantial training, posing adoption challenges.

2 Data and methodology used to track the demand for digital and AI skills in health occupations and in the sector

Web platforms like LinkedIn, Monster, Indeed, ZipRecruiter, and CareerBuilder are used globally by job seekers to find new opportunities in the labour market. These tools aggregate job listings, creating a comprehensive “electronic labour market” where numerous new positions are posted daily. The rise of web scraping technology now allows for the automated collection and analysis of information from these postings, providing valuable insights into labour market dynamics and skill needs.

Data from online job postings offer several advantages over traditional labour market data, particularly in terms of timeliness and granularity. Because they are collected on a continuous basis, they are especially useful for identifying emerging trends in skills and technology demands. The current study leverages a comprehensive database from Lightcast, which gathers millions of job postings from thousands of sources daily. The data collected include a wide range of variables, such as skill keywords, qualifications, geographic locations, employers, contract types, and, where available, salary information.[5]

2.1. The health occupations analysed in this paper and the taxonomies used

The empirical analysis in this study leverages the Lightcast® Occupation Taxonomy (LOT) and the North American Industry Classification System (NAICS) classification available in Lightcast databases. This methodological approach allows for the systematic extraction of relevant job postings, which were subsequently categorised into two primary groups (see Annex A for more information):

- **Health Occupations**: This category encompasses all roles classified under the career area code 20 – Healthcare within the LOT framework. This category includes a range of professions devoted to health-related services, demanding both technical healthcare and patient-centred skills.
- **Other Occupations in the Health Sector**: This category comprises all roles classified under NAICS code 63 – Health industry, excluding those classified in the LOT code 20 – healthcare. It encompasses roles that are not directly involved in patient care or clinical support but are essential for the operation of healthcare facilities. Examples include data analysts, administrative staff, finance professionals, etc. These positions are advertised for recruitment in hospitals and other health settings but do not require clinical qualifications.

These occupational categories are analysed separately to disentangle the specific demands within the health industry.

2.2. Identification of digital skills from online job postings

Online Job Postings (OJPs) offer a wealth of detailed and granular information on the specific skill demands within the health sector and the analysis of OJPs can uncover the evolving requirements for digital, AI, and other technology-related skills.

The LOT framework organises skills into 31 categories and over 440 subcategories. For the purposes of this study the analysis concentrated on four categories encompassing IT, digital, and technology skills, ensuring a targeted examination of the relevant competencies (see Annex A). Additionally, this study also analysed digital-related subcategories from the health skill category (e.g. Clinical Informatics). With the resulting skills contained in the selected subcategories, a classification rule was applied that consists of selecting those new job advertisements where at least 2 digital skills are mentioned in the job description.[6]

2.3. Identification of AI-related skills from online job postings

To identify AI-related skills and job postings in the health sector, the study employed a comprehensive methodology using the LOT framework. In particular, the approach involved the extraction and classification of AI-related job postings based on a detailed list of AI-related keywords. The list of keywords, which includes 309 distinct skills grouped into seven clusters, was derived from existing literature (Borgonovi et al., 2023[13]) and supplemented with additional terms.

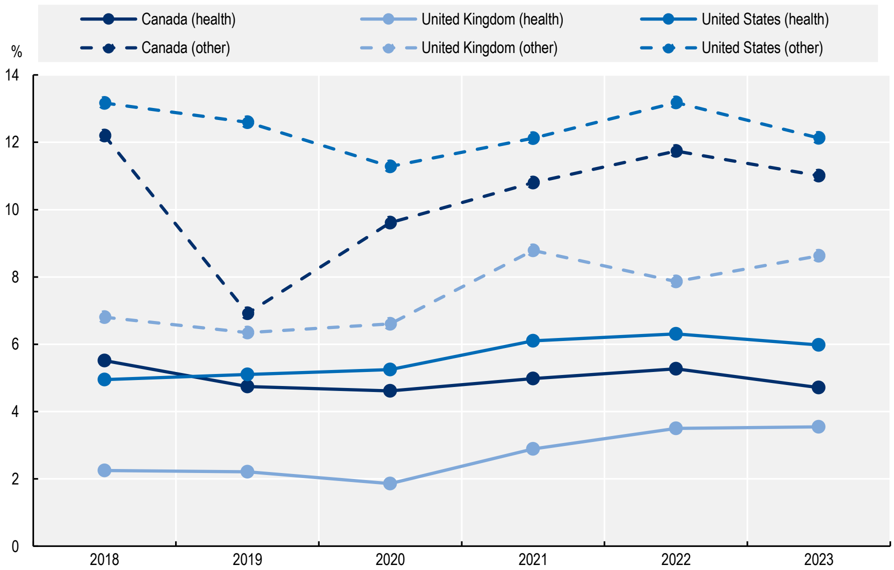
The AI-related skills were categorised into seven clusters, each representing a specific domain of AI applications. This structured approach ensured that the analysis captured the diverse range of competencies required in the health sector. Each AI skill was also classified as generic or specific following Borgonovi et al. (2023[13]). Generic skills refer to those AI skills that can be common in roles using AI systems but not necessarily developing them. These include, for instance, applications of artificial intelligence or sentiment analysis. In contrast, specific skills include AI skills related with more specific applications or methods, such as gaussian process, transformers or Apache Spark. This document considers a job posting as AI-related if it includes at least one specific or two generic AI skills. The clusters and some of their representative skills are discussed in Annex A.

3 Trends in the demand for digital professionals in the health sector

The empirical analysis of OJPs reveals some interesting trends in the demand for digital and AI-related professionals in the health sector. Results in Figure 1 across the three countries included in the analysis indicate that digital-related job postings account for approximately 2% to 6% of total vacancies in health occupations, represented by solid lines in the chart. This share has shown a slight positive trend after 2020 in both the United Kingdom and the United States, but not in Canada. Digital OJPs in other occupations within the health sector, depicted by dashed lines, account for approximately 6% to 13% of total OJPs in this group, a relatively larger share of job postings over the total, with the data showing a trend increase in the United Kingdom, but not in Canada and the United States.

Figure 1. Digital-related job postings

As percentage of total job postings for each country



Note: Job postings were classified as digital related if at least two digital skills (see Annex A) are listed in the skill requirements extracted by Lightcast from the original text. The figure above shows two groups for each country: 1) health occupations (health) as classified by the occupation taxonomy and 2) other occupations in the health sector (other), comprising non-health occupations working in enterprises classified in the NAICS health sector.
Source: OECD based on Lightcast data.

In the United States, digital-related job postings in health occupations exhibit a consistent upward trajectory, peaking in 2022 before a slight decline in 2023. This result suggests an increasing recognition of the importance of digital skills in enhancing health delivery and management. The US health sector has been particularly proactive in adopting digital health technologies, driven by policy initiatives like the Health Information Technology for Economic and Clinical Health (HITECH) Act, which incentivised the adoption of EHRs (see Box 2).

Box 2. The HITECH act as a driver of digital skills adoption

The Health Information Technology for Economic and Clinical Health (HITECH) Act, part of the American Recovery and Reinvestment Act of 2009, significantly advanced the adoption of digital technologies in US health. The Act allocated substantial financial incentives to encourage the implementation of EHRs and other digital health tools. The HITECH Act introduced several critical components:

- Financial Incentives: Up to USD 27 billion in Medicare and Medicaid incentives were provided to health providers demonstrating meaningful use of certified EHR technology. These incentives aimed to offset EHR adoption costs and promote widespread implementation.
- Certification Standards: The Act mandated certification standards for EHR systems to ensure their functionality, security, and interoperability, facilitating seamless health information exchange across different health settings.
- Meaningful Use Criteria: Providers were required to demonstrate the effective use of EHRs to improve patient care, including objectives like electronic prescribing, health information exchange, and clinical decision support.
- Health Information Exchange (HIE): Funding was provided to develop and expand HIE infrastructure, enabling secure sharing of health information among providers, enhancing care co-ordination, and reducing service duplication.

The HITECH Act has considerably increased the adoption of digital technologies in US health. By 2017, nearly 96% of hospitals and 80% of office-based physicians had adopted EHR systems, a significant rise from pre-HITECH levels. The widespread use of EHRs has improved documentation efficiency, patient information access, and care co-ordination. Similarly, US NIH maintains clinicaltrials.gov and BioLINCC to support research by providing a database of clinical studies. This includes processes and safeguards for access to and sharing of data.

Source: www.hipaajournal.com/what-is-the-hitech-act/, www.healthit.gov/data/quickstats/office-based-physician-electronic-health-record-adoption; Office of the National Co-ordinator for Health Information Technology (ONC) (2017), "Office-based Physician Electronic Health Record Adoption." Retrieved from Health IT Dashboard; Office of the National Co-ordinator for Health Information Technology (ONC) (2017), "Hospital Electronic Health Record Adoption." Retrieved from Health IT Dashboard.

The results for the United Kingdom mirror the US trend, showing a gradual increase in the share of digital-related job postings in health occupations. This also reflects the United Kingdom's commitment to digital transformation in health, underscored by the National Health Service's (NHS) Long Term Plan (Box 3), which prioritises digital innovations to improve patient care and system efficiency. The rise in digital job postings in the United Kingdom indicates a sustained investment in health IT infrastructure and a strategic focus on integrating digital tools in clinical workflows.

Box 3. The NHS Long Term Plan and its relation to digital technology adoption

The National Health Service (NHS) Long Term Plan, launched in January 2019, is a comprehensive strategic initiative aimed at improving the health system in England over the next decade. The plan outlines a series of ambitious goals designed to address the challenges facing the NHS and ensure the provision of high-quality, sustainable health services.

Among the key components of the NHS Long Term Plan there are elements of workforce development, designed to address workforce challenges. The plan includes measures to recruit, train, and retain health professionals, ensuring that the NHS can meet future demands. Similarly, much emphasis is put on measure to spur the digital transformation. A central pillar of the Long Term Plan is the adoption of digital technologies to enhance patient care and operational efficiency. This includes the widespread use of EHRs, digital consultations, and health apps.

The digital transformation initiatives outlined in the NHS Long Term Plan are integral to achieving its broader goals. By investing in digital technologies, the NHS aims to improve patient outcomes, streamline operations, and make health more accessible. The plan envisions a future where digital tools enable better patient engagement, more accurate diagnoses, and personalised treatment plans. For example, the use of EHRs and digital consultations can reduce administrative burdens, enhance care co-ordination, and provide patients with more convenient access to health services.

Source: www.longtermplan.nhs.uk/areas-of-work/digital-transformation/.

In Canada, the data on OJPs in health occupations reveal a more stable share of digital-related job postings compared to the United Kingdom and the United States. However, the sector-specific results (i.e. the share of OJPs for digital professionals in the sector) show a positive trend, pointing to an overall increasing demand for digital skill in non-clinical roles within the Canadian health sector in most recent years.

The expansion in the demand for non-clinical occupations in the health sector includes administrative, IT, and support functions critical to modern health systems. The increasing demand for digital skills across diverse health roles reflects the sector’s transition towards a more data-driven and technologically integrated environment, aligning with global trends in digital health innovation.

4 Trends in AI-related job postings: What is the demand for AI professionals in health occupations and in the health sector?

Within the group of digital occupations, this study also identifies those that require AI-related skills specifically. Compared to the rest of the economy, the demand for professionals with AI skills in the health sector remains relatively low. Figure 2A shows the evolution of AI-related job postings by industry across 16 English-speaking and European countries. The health sector (0.8%, on average) falls below the economy-wide average over the four-year period (dotted line, 2.7%). Notably, only 6 out of the 18 industries in Figure 2A are above this average, highlighting the specialised nature of AI skills in the labour market.

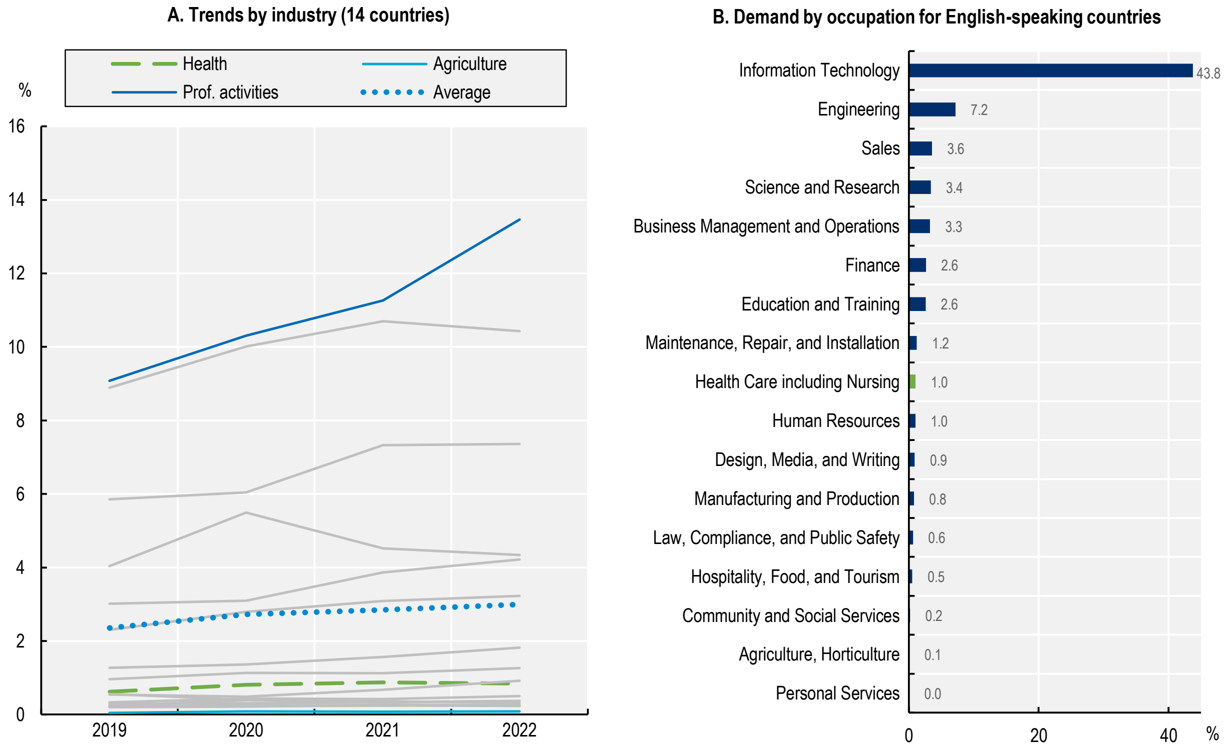
An examination of the demand for AI skills in job postings for selected occupations across English-speaking countries also shows a relatively low demand of AI skills in healthcare occupations (1.0% in Figure 2B). Nevertheless, this share is not too far behind other occupational groups at the forefront of AI adoption (excluding IT and engineering groups that are more closely linked to AI development), such as science and research (3.4%), business management (3.3%) and finance (2.6%).

These comparisons suggests that, although the demand for AI skills in healthcare lags behind the economy-wide average, it is not uniquely underrepresented compared to other sectors and occupations. As AI becomes more integrated across industries, shifts in healthcare demand for AI skills may follow, reflecting the increasing demand observed in other areas of the labour market.

Against this backdrop, this section explores more country-specific trends in the demand for professionals with AI skills in health occupations and other occupations in the health sector for Canada, the United Kingdom and the United States.

Figure 2. Share of OJPs requiring AI skills (2019-22)

Percentage of OJPs advertising positions requiring AI skills, by (A) industry and year, (B) occupation



Note: Figure A shows the percentage of AI online job postings in a given year, by industry, averaged across 14 European and English-speaking countries. The dotted line is the average across all industries, thin grey lines portray the average of other industries for comparison purposes. The industries with the lowest and highest average share of AI online job postings are highlighted in the figure. Figure B shows the percentage of AI online vacancies in specific occupations for English-speaking countries (Australia, Canada, New Zealand, the United Kingdom, the United States). Occupations are sorted in descending order by the share of vacancies requiring AI skills.
Source: Authors' elaboration based on Borgonovi et al. (2023[13]) calculations and Lightcast data.

Data in Figure 3 indicate that AI-related job postings have remained relatively stable between 2018 and 2023 at 0.2% to 0.3% of total OJPs in health occupations across the three countries analysed. In contrast, the share of AI-related vacancies in other occupations within the health sector shows significant increases in Canada and the United States, but not in the United Kingdom where there have been substantial fluctuations from year to year. These shares are much smaller when compared to the share of all digital jobs advertised for health professionals and other occupations in the health sector (further details on the interpretation of these results are in Box 4).

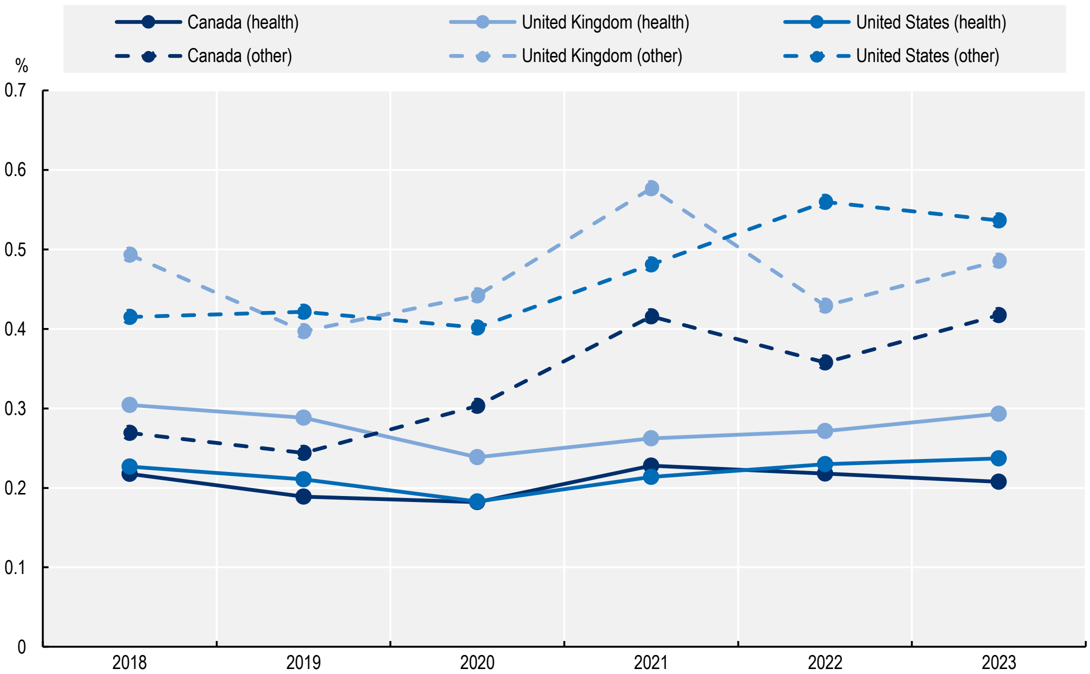
Box 4. AI, its direct demand and the adoption in the workplace

It is important to note that Figure 3 tracks the evolution of new job postings that explicitly mention AI-related skills rather than providing an assessment of the penetration of AI technologies into the health professions. This is to say that these results specifically reflect the intensity with which AI-related skills are sought in job postings, indicating the level by which AI is developed within the health sector. These results, therefore, portray the intensity of "direct" AI skill demand (i.e. how much of AI, machine learning etc. health professionals should know) but do not measure how extensively AI technologies are currently being used in health practices (e.g. whether an hospital has implemented a AI-powered HR system or integrated AI chatbots in their websites). The discussion on the intensity of AI adoption in health workplaces, including how AI technologies could be used in everyday health operations, is addressed later in this paper when shifting the discussion from the demand for AI skills to the potential application and integration of AI technologies within the health sector.

Results indicate that, in the United States, the share of AI-related job postings in health occupations has shown a steady, albeit modest, increase. This suggests that while AI is being integrated into health, its development is primarily in specific niches rather than widespread across all clinical roles. However, the demand for AI skills in job postings in the health sector indicates broader applications of AI technologies in areas such as health management, administrative automation, and research. This aligns with the growing interest in leveraging AI for operational efficiencies and enhanced decision-making processes within health organisations.

Figure 3. AI-related job postings in health occupations and other occupations in the health sector

As percentage of total job postings for each country



Note: Job postings were classified as AI related if at least two generic or one specific AI skill (see Annex A) are listed in the skill requirements extracted by Lightcast from the original text. The figure above shows two groups for each country: 1) health occupations (health) as classified by the occupation taxonomy and 2) other occupations in the health sector (other), comprising non-health occupations working in the NAICS health sector.
Source: OECD based on Lightcast data.

Along these lines, Canada exhibits a notable increase in AI-related job postings within the health sector rather than in health occupations. This suggests a growing emphasis on AI capabilities in non-clinical functions within the health sector, such as data analytics, predictive modelling, and administrative automation.

In contrast, the trend for AI-related job postings in both health occupations and other health sector roles in the United Kingdom fluctuates over time, remaining overall relatively flat over the period. Results also suggest a relatively slower adoption of AI technologies compared to North American counterparts. Potential factors could include regulatory barriers, slower integration of AI into clinical practice, and cautious adoption due to concerns about data privacy and ethical considerations in AI deployment.

The modest share of AI-related job postings in health occupations suggests that the direct integration of AI in direct patient care roles is still in its nascent stages and that only a handful of jobs in this area do require explicitly skills/knowledge on how to develop AI systems. However, the significant growth in AI-related postings in other health sector roles highlights the potentially transformative potential of AI in areas such as health management, administration, and research. While growth in this area has been fast, it is also notable that the overall demand level remains relatively small.

5 Analysis of digital skill demands in health occupations

Previous sections of this paper have assessed the demand for digital and AI professionals. The analysis in this section, instead, provides information on the various types of digital and AI skills that are in high demand in health roles,[7] shedding light on what technologies and tools are most demanded in new digital/AI health jobs. Figure 4 presents a detailed breakdown of the share of digital OJPs mentioning at least one skill from the ten most mentioned digital skills subcategories[8] by occupational groups (health occupations and other occupations in the health sector).

5.1. Canada

The data in Figure 4 show that among digital health occupations, skills such as Health Information Management/Medical Records, Computer Science, and Data Analysis are frequently demanded by employers. Over the periods from 2018-19 to 2022-23 results show that approximately 35% of health job postings mentioning digital skills required knowledge of Health Information Management/Medical Records in the job description, with this proportion being relatively stable in recent years, reflecting the critical importance of managing patient data efficiently in modern health occupations. Also, the results show that the demand for Computer Science skills has been strong throughout the period, with 30% of new job digital-related postings being published in this area over the period. Similarly, much of the demand for digital skills in health occupation focused also on Data Analysis skills, suggesting an increasing integration of digital technologies in patient care and administrative processes.

Results also show a marked increase in the share of OJPs in Canada demanding data collection and clinical informatics skills (see Box 5).

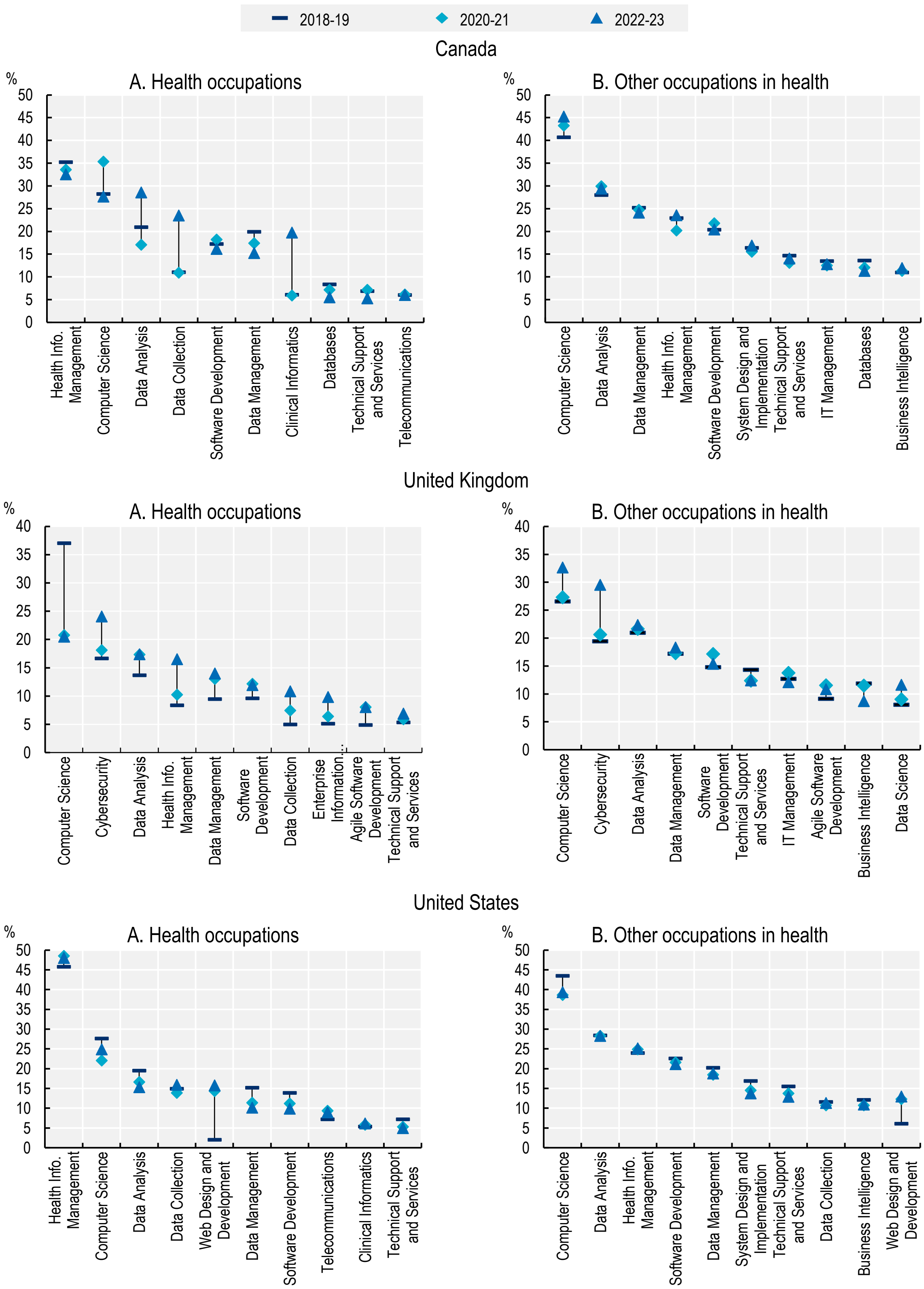
In other occupations within the health sector in Canada, the share of OJPs mentioning digital skills is similarly significant. Skills in Computer Science, Data Analysis, and Data Management are prominently mentioned, highlighting the diverse applications of digital technologies beyond clinical roles. In particular, the consistent demand for Data as well as IT Management skills reflects the necessity for robust digital infrastructure to support health operations.

5.2. United Kingdom

The analysis of digital skill categories in job postings within the United Kingdom health sector highlights significant trends in the demand for digital competencies across health roles and related fields (see Figure 4). In health occupations, a considerable share of digital-related OJPs mentions at least one skill from the top ten digital subcategories. Skills such as Computer Science, Cybersecurity, and Data Analysis are frequently mentioned by employers looking for health professionals with digital skills. That being said, from 2018-19 to 2022-23, there has been a noticeable shift in the demand for these skills. For instance, the share of health professionals requiring Computer Science skills, while initially high at 37%, has stabilised around 20.5% in recent years.

Conversely, the demand for Cybersecurity skills has significantly increased, rising from 16.6% of digital OJPs for health professionals in 2018-19 to 24.1% in 2022-23. This surge reflects the growing importance of protecting sensitive health data from cyber threats, especially with the increasing digitisation of health records and the broader use of telehealth services. These results highlight that health providers in the United Kingdom are likely prioritising cybersecurity measures to safeguard patient information and ensure compliance with stringent data protection regulations.

Figure 4. Share of OJPs mentioning at least one skill from top 10 digital subcategories



Note: The ten most mentioned skills were defined according to the annual average mentions between 2018 and 2023. The name of the skill Health Information Management and Medical Records was shortened in the figure as Health Info. Management.
Source: OECD based on Lightcast data

Box 5. Rising demand for data collection and clinical informatics skills in health occupations in Canada

The analysis of OJPs in the Canadian health sector reveals a notable increase in the demand for skills in data collection and clinical informatics. This trend reflects the growing importance of data-driven decision-making and advanced data management in modern health practices.

Data Collection Skills

The share of OJPs mentioning data collection skills has significantly increased over recent years. This rise is indicative of the health industry's shift towards more systematic and comprehensive data gathering methods. Effective data collection is essential for various health functions, including patient monitoring, research, and quality improvement initiatives. For instance, health providers are increasingly using EHRs and other digital tools to collect and store patient data accurately. This data serves as a foundation for analysing health trends, identifying patient needs, and developing personalised treatment plans.

In practice, health professionals equipped with robust data collection skills are better positioned to contribute to initiatives like population health management and epidemiological studies. The ability to gather, validate, and utilise data efficiently ensures that health organisations can maintain high standards of care and respond proactively to emerging health issues. Increasingly, also, as new AI technologies are deployed, it is expected that skills required to ensure the data quality/accountability are likely to become important when designing digital technologies including AI.

Clinical Informatics Skills

Similarly, the demand for clinical informatics skills has seen a substantial rise. Clinical informatics involves the application of information technology to organise and analyse health data, thereby enhancing clinical workflows and decision-making processes. Professionals in this field leverage tools such as clinical decision support systems, health information exchanges, and interoperability solutions to improve patient care.

The growing emphasis on clinical informatics is driven by the need to integrate diverse health information systems and facilitate seamless data exchange between different health providers. For example, clinical informatics specialists play a crucial role in implementing and optimising EHR systems, ensuring that critical patient information is accessible and actionable across various care settings.

Overall, the increased demand for data collection and clinical informatics skills underscores the health sector's commitment to leveraging technology to enhance patient outcomes, streamline operations, and foster a more efficient and responsive health system. These skills are pivotal in advancing the digital transformation of health, enabling providers to deliver high-quality, data-informed care.

Similarly, the demand for Data Analysis skills has seen a steady increase, moving from 13.7% to 17.4% of total digital OJPs for health professionals. This trend underscores the importance of leveraging data analytics to enhance clinical decision-making and operational efficiency.

In other health sector occupations, the share of OJPs mentioning digital skills shows varying intensities. Notable skills other than those discussed above include Data Management, Software Development, and Technical Support and Services.

5.3. United States

The analysis of job postings in the United States reveals notable trends in the demand for various digital competencies across health roles and related fields (see Figure 4).

In health occupations, Health Information Management/Medical Records consistently shows the highest share of mentions among digital skills. Approximately 45.8% in 2018-19 to 48.0% in 2022-23 OJPs for digital health professionals directly mentioned this competence in the United States. The sustained demand underscores the critical importance of efficiently managing patient data and maintaining accurate medical records. As health providers increasingly adopt electronic health records (EHRs), the need for professionals skilled in health information management continues to grow.

The demand for Computer Science skills, while initially prominent in 2018-19, experienced a slight dip to 22.1% of digital OJPs for health professionals in 2020-21 before recovering to 24.9% in 2022-23. Despite that, the results signal the increasing integration of digital technologies in health and the need for foundational technical skills to support various IT functions within health settings.

The demand for Data Analysis skills, instead, shows a slightly declining trend from 19.5% in 2018-19 to 15.3% in 2022-23 of digital OJPs mentioning this specific competence. This decrease might indicate a stabilisation in the initial surge of demand as data analytics tools become more embedded in health operations. Despite the slight decline, the overall demand remains substantial, highlighting the importance of data-driven decision-making in clinical and administrative functions.

Data Collection skills have shown an increase in demand. This growth indicates a rising emphasis on systematic data gathering to support clinical research, patient monitoring, and quality improvement initiatives. Other digital skill such as Data Management, Software Development or Telecommunications have experienced small fluctuations in demand over time.

When analysing other health sector occupations, Computer Science consistently shows the highest share of mentions among digital skills, albeit with some fluctuations. The share of digital OJPs mentioning Computer Science skills was 43.5% in 2018-19, decreased slightly to 38.6% in 2020-21, and then increased to 39.3% in 2022-23. This trend indicates a sustained demand for foundational technical skills to support various IT functions within health organisations. The need for professionals skilled in computer science remains critical for maintaining and advancing health IT infrastructure, ensuring robust data management, and supporting the deployment of new technologies.

Health Information Management/Medical Records is another skill category that has seen consistent demand. The share of OJPs mentioning these skills has increased from 24.0% in 2018-19 to 25.1% in 2022-23. This trend reflects the ongoing importance of efficiently managing patient data and maintaining accurate medical records, particularly as health providers continue to adopt and integrate electronic health records (EHRs). The need for professionals who can navigate and optimise these systems is crucial for improving patient care and operational efficiency.

6 Fast-growing digital skill subcategories

The analysis in Figure 5 also identifies fast-growing digital skill subcategories within both health occupations and other health sector roles.

The results show some common trends across the three countries. Among health occupations, Clinical Informatics (in Canada and the United Kingdom), and Video and Web Conferencing have shown significant growth. Clinical Informatics combines data, information technology, and health to optimise the acquisition, storage, retrieval, and use of health information for better patient care and improved health outcomes. For instance, Clinical Informatics showed an average annual growth rate of 89.6% and an average annual share of 5.9% OJPs mentioning this skill in the UK health labour market. This increase reflects the growing need for health professionals who can manage and analyse clinical data to improve patient care and highlights the importance of integrating electronic health records (EHRs) and other digital tools to support clinical decision-making and streamline health delivery.

Video and Web Conferencing skills have also become particularly relevant in both clinical and non-clinical roles in the three countries, as the COVID-19 pandemic accelerated the adoption of telehealth services. Health professionals now routinely use video conferencing tools to conduct remote consultations and ensure continuity of care. In the United States, for instance, Video and Web Conferencing skills have seen significant growth in other occupations in the health sector, with an average annual growth rate of 56.8% and an average annual share of 1.8%.

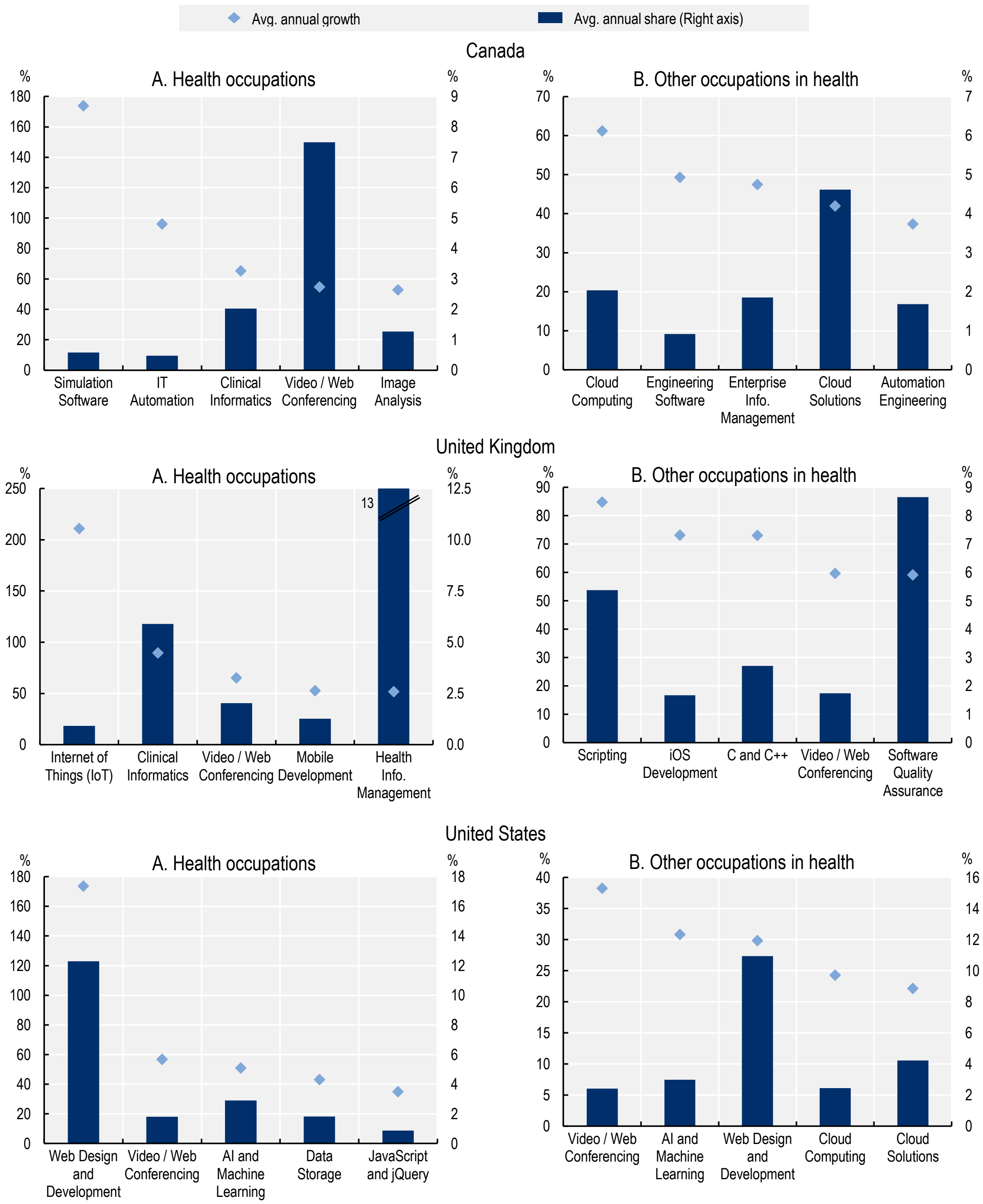
Cloud Computing and Cloud Solutions have also become more demanded in other occupations in the health sector in Canada and the United States. The rise in skills associated with cloud-based technologies reflects the shift towards digital and remote solutions for data storage and management, enabling more flexible and scalable health operations. For instance, Cloud Computing is vital for enabling telehealth platforms that require secure, scalable storage solutions for patient data.

Other country-specific trends are also visible in the analysis. Among health occupations in Canada, Simulation Software and IT Automation have shown significant growth, although these two skills started from a very low base. The surge in demand for these skills can be attributed to the increasing use of these technologies for medical training and IT automation for streamlining clinical workflows. In other health sector occupations in Canada, the fastest-growing subcategories include Engineering Software, and Automation Engineering. These skills are essential for developing and maintaining advanced medical devices and automated systems used in health facilities. Automation Engineering skills are critical for the development of robotic systems used in surgeries and other medical procedures, enhancing precision and efficiency.

In the United Kingdom, the analysis identifies several fast-growing digital skill subcategories within both health occupations and other health sector roles, highlighting the dynamic nature of digital skill demands driven by technological advancements and evolving health needs (see Figure 5). In health occupations, the Internet of Things (IoT) stands out with an exceptional average annual growth rate of 210.9%, although the average annual share of OJPs demanding this skill remains relatively low at 0.9%, something that is also likely to inflate its growth rate. This rapid growth underscores the emerging recognition of the value of connected medical devices, which enhance patient monitoring, improve data accuracy, and facilitate real-time health management. For instance, IoT-enabled devices such as smart insulin pens and remote cardiac monitors allow health providers to continuously monitor patients and adjust treatments based on real-time data.

Figure 5. Fast-growing skill subcategories

Skill categories with the highest average annual growth in demand between 2018 and 2023



Source: OECD based on Lightcast data.

In the United States, Web Design and Development stands out as the fastest-growing digital skill category in health occupations and the third in other occupations in the sector. In particular, for health occupations, this group of skills showed an impressive average annual growth rate of 173.7% and an average annual share of 12.3% (see Figure 5). This substantial increase in demand reflects the growing emphasis on enhancing online presence and digital health services. This trend is driven by the need to meet the evolving demands of patients and health providers for accessible, efficient, and integrated digital health solutions.

Similarly, for other occupations in the United States health sector, AI and Machine Learning skills are increasingly in demand, with an average annual growth rate of 51.0% and an average annual share of 2.9%. The integration of AI and machine learning technologies into health is transforming various aspects of patient care, from diagnostic processes to personalised treatment plans. Health organisations are leveraging these technologies to enhance clinical decision-making, improve patient outcomes, and optimise operational efficiencies. For example, AI algorithms are being used to analyse medical images, predict patient risks, and streamline administrative tasks. In addition, Data Storage skills, JavaScript and jQuery skills have also shown notable growth over the period, signalling how the increasing volume of health data necessitates robust data storage solutions to ensure secure, scalable, and efficient data management and the development of interactive web applications that enhance user experience and facilitate digital health initiatives.

7 The potential for automation of health occupations in the United States

The potential transformative role of AI in health is widely recognised, yet its direct manifestation in the labour market, as indicated by AI skill demands in OJPs, appears, so far, limited. Previous sections of this report highlighted that while digital skills such as electronic medical records and data analysis are increasingly demanded, explicit mentions of AI skills remain relatively sparse. This discrepancy suggests that the transformative impact of AI[9] in health is more likely to be realised through the adoption and integration of AI technologies in existing tasks rather than the development of AI-specific roles within the health sector, the former not directly picked up in the analysis of OJPs.

This is to say that the integration of AI into health tasks may pass unperceived in the analysis of OJPs because vacancies might not explicitly mention AI technologies, even though firms are actively adopting these innovations. This phenomenon can be attributed to several factors.

Firstly, AI technologies often enhance existing roles and responsibilities rather than creating entirely new job categories or roles. For example, a job posting for a radiologist may not specifically mention AI, but the role may involve using AI-powered diagnostic tools to interpret medical images. Similarly, a position for a nurse may not explicitly reference AI, yet the nurse might use AI-driven systems for patient monitoring and care management. These tools are integrated into the routine workflow, making AI a part of the job's daily tasks rather than a distinct requirement.

Secondly, employers might assume that AI-related skills are implicit within broader skill categories. For instance, a job posting for a health administrator might list requirements such as "proficiency in electronic health record (EHR) systems" or "experience with advanced data analysis." These descriptions encompass the use of AI technologies without explicitly naming them. As AI becomes more embedded in health operations, its presence might be taken for granted, leading to fewer direct mentions in job postings.

Thirdly, firms might focus on the outcomes enabled by AI rather than the technology itself in job postings. For example, a job ad might emphasise "improved diagnostic accuracy" or "enhanced patient care efficiency," outcomes that AI helps achieve, without specifying the AI tools used to reach these goals. This focus on results rather than the means can obscure the presence of AI in job postings.

Additionally, the adoption of AI can be a top-down process where organisational leaders decide to implement AI systems across various departments. In such cases, the emphasis in job postings may remain on traditional skills and qualifications, while AI tools are provided as part of the workplace environment. Employees may receive training on these systems after being hired, further reducing the necessity to mention AI explicitly in the job ad. For example, a hospital might adopt AI-based predictive analytics to optimise patient flow and resource allocation. The job postings for hospital administrators or operations managers may not explicitly state "AI" or "predictive analytics," but these technologies will be integral to the job's responsibilities. As a result, while AI significantly influences the role, it remains unmentioned in the job description.

This section aims at analysing the potential for automation of health occupations through both AI and robotics technologies. This analysis is key for several reasons. It is widely recognised that AI adoption in health has the potential to significantly enhance productivity, streamline operations, and mitigate labour shortages, which are persistent challenges in the US health system as in other OECD countries. Automation through AI can handle repetitive and time-consuming tasks, allowing health professionals to focus on more complex and patient-centred aspects of care. For example, AI algorithms can process vast amounts of medical data to assist in diagnostics, predict patient outcomes, and personalise treatment plans. Tools like DeepMind Health are already demonstrating these capabilities, providing valuable support to clinicians and improving the accuracy and efficiency of patient care.

The potential for automation extends across various health occupations. In administrative roles, AI can automate scheduling, billing, and patient communication, reducing the administrative burden on health staff. In clinical settings, AI-powered diagnostic tools can assist radiologists in interpreting medical images, identify anomalies in pathology slides, and predict patient deterioration through continuous monitoring. Surgical robots, guided by AI, can enhance precision and reduce recovery times. These advancements illustrate the broad spectrum of AI applications that can transform health delivery.

However, the integration of AI into health workflows is not without challenges. Successful adoption requires not only technological readiness but also a workforce capable of effectively utilising these advanced tools. Health professionals need to be adequately trained to understand and trust AI systems, ensuring that these technologies are used to their full potential. A recent study aimed to understand the benefits and challenges of human-AI collaboration conducted an experiment in which AI assistance for professional radiologists is randomly selected (Agarwal et al., 2023[14]). The study shows that despite the AI tool itself performs better than most of the radiologists, giving radiologists access to AI predictions does not lead to an overall higher performance and implies a significant increase in time for professional to make a decision. This example highlights the need for comprehensive training programmes and ongoing professional development to equip workers with the necessary skills and confidence to work alongside AI.

Moreover, the ethical implications of AI in health must be carefully considered. Issues such as data privacy, algorithmic bias, and the transparency of AI decision-making processes are critical to maintaining patient trust and ensuring equitable care. Policy makers and health organisations must establish robust frameworks to address these concerns, balancing innovation with ethical responsibility.

8 Estimating O*NET task-level potential automatability scores

This section outlines the methodology employed to estimate the potential automatability of health occupations using large language models (LLMs). Specifically, the study leverages the US O*NET occupational structure, which provides detailed descriptions of tasks across various health occupations.

The methodology for assessing the potential automatability of these tasks employs LLMs to generate task-level potential automatability scores. This approach builds on the methodology developed by Eloundou et al. (2023[15]), Eisfeldt et al. (2023[16]), and the ILO Research Department (2023[17]), which involves assessing tasks' exposure to AI technologies using LLMs. Differently from previous literature mentioned above, however, two specific automating technologies, rather than one, are considered in this study: Generative AI (GenAI) and Advanced Robots (AR) (see Box 6 on these concepts).[10] The studies mentioned above have faced some methodological critiques including, in particular, the insufficient consideration of contextual factors by Large Language Models (LLMs) as those may not fully grasp the nuances of various jobs, underscoring the necessity for human oversight to ensure accurate assessments. That being said, most of this literature has demonstrated the reliability of its approach by performing robustness checks using human-annotated rankings, ensuring the accuracy of task-level assessments. This validation supports the credibility of using large language models (LLMs) for analysing AI exposure. Moreover, the approach is highly scalable, enabling the analysis of thousands of tasks efficiently without the limitations of human cognitive overload, making it a practical and comprehensive tool for understanding AI's impact on labour markets.

In this paper, the process to assess the likelihood for automatability of each task involves using sequential API calls to the LLM for evaluating the potential for a given core task to be automated by either GenAI or AR. For each task, the model receives a detailed description of the task and is asked to provide an automation score ranging from 0 to 1. This score reflects the likelihood that the task can be automated by the specified technology (see Annex C for more details).

Box 6. Defining Generative AI and advanced robots

This analysis in this section focuses on the potential impact played by Generative AI and Advanced Robots on health occupations. These two technologies have the potential to reshape industries and societies, presenting opportunities and challenges. For this paper, these concepts are defined as:

Generative Artificial Intelligence (GenAI)

GenAI uses techniques like deep learning and neural networks to produce new data forms. Unlike generic AI, which primarily focuses on tasks involving classification, prediction, or detection, GenAI actively creates new content based on the patterns it learned from existing data used during training. Examples of GenAI technologies are text-to-image generators and LLMs, which are increasingly used in tasks such as translation and interpretation, creation of intelligent chatbots, coding and content creation, etc. With new radical advancements in this area, the analysis of GenAI rather than simpler forms of AI warrants a better understanding of recent dynamics.

Advanced Robots

Advanced Robots are automated machines which are able, to some extent, to operate in complex environments and rely less on human intervention. The advanced characteristic of this type of robots is generally linked to the use of software and hardware that enhances robots' problem-solving, mobility, resistance, sensorial and intelligence capabilities. For example, the introduction of cutting-edge sensors and actuators contributes to create robots with precise responses to obstacles and challenges.

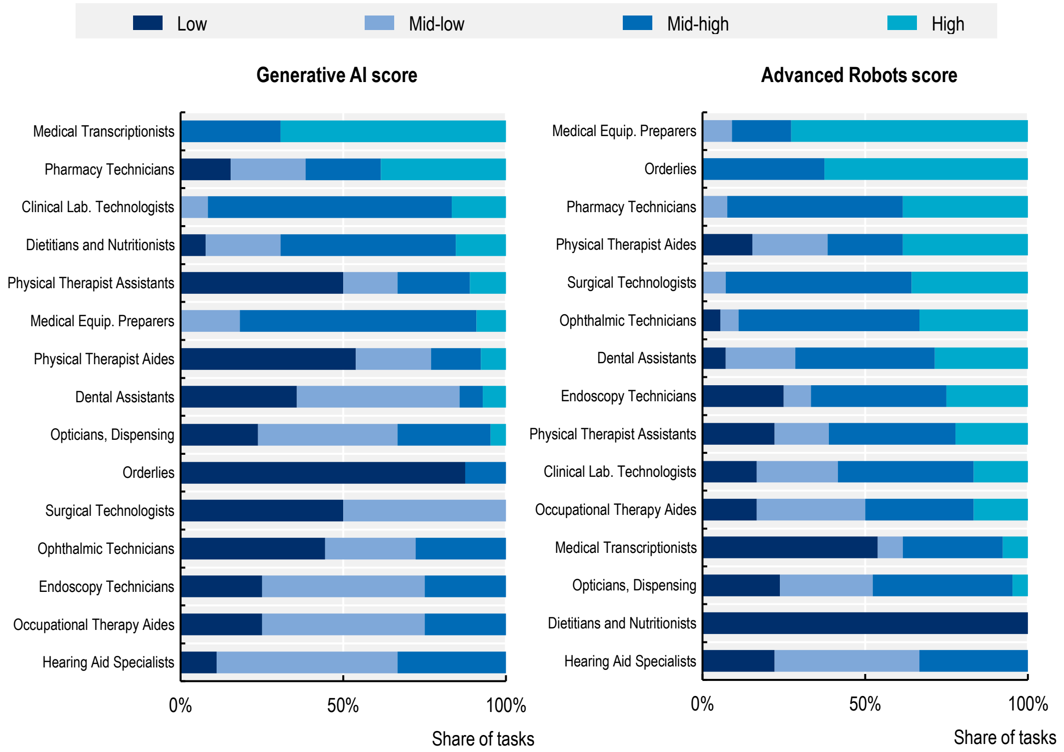
Source: OECD.AI. (2024) Generative AI. https://oecd.ai/en/genai/issues/overview; Hinojosa, J. and Potau X. (2017[18]) Advanced industrial robotics: Taking human-robot collaboration to the next level. www.eurofound.europa.eu/system/files/2019-12/wpfomeef18003.pdf

8.1. Occupation level automatability of health professions

The occupation-level analysis provides a comprehensive view of how tasks within specific roles are susceptible to automation by GenAI and AR. The share of tasks classified into different automatability groups (low, mid-low, mid-high, and high), based on the score assigned, reveals the varying impact of these technologies across health occupations.

For Generative AI, the share of tasks in the high automatability category varies significantly across occupations (see Figure 6). For instance, Medical Transcriptionists[11] show a high automatability score for 69% of their tasks, reflecting the substantial potential for automation in this occupation. This is due to the repetitive and text-based nature of transcription tasks, which can be efficiently handled by AI technologies.

Figure 6. Likelihood of task automatability by occupation in the United States



Note: The figure shows, for selected occupations, the share of tasks classified into four main groups depending on the automatability score: Low (score 0.00 – 0.25), Mid-low (0.25 – 0.50), Mid-high (0.50 – 0.75) and High (0.75 – 1.00).
Source: Authors' calculations based on sequential calls to the GPT4 model through the OpenAI API and O*NET data.

Results for Pharmacy Technicians also classify 38.5% of their tasks as highly automatable, suggesting that dispensing medication and managing inventory could be increasingly managed by AI systems. In contrast, Orderlies[12] have a higher share of tasks in the low automatability category (87.5%), suggesting that the nature of their work, which often involves physical tasks and direct patient care, is less susceptible to automation by GenAI tools. Similarly, Occupational Therapy Aides have a significant portion of tasks in the mid-low category (50%), reflecting the hands-on and patient-interaction aspects of their roles that are challenging to automate.

GenAI is not the only technology that can lead to automation. The adoption of advanced robots, which overcome some of the physical limitation of GenAI can have significant impact on an occupation's automatability. The results on the automatability which could be potentially driven by Advanced Robots show different patterns from GenAI's results. Pharmacy Technicians and Medical Equipment Preparers, for instance, have a significant share of tasks in the high automatability category (38.5% and 72.7% respectively), indicating that many of their tasks could be automated using robotic technologies. These tasks often involve precise but repetitive actions, such as preparing medication or handling medical equipment, which are well-suited to robotic automation.

Surgical Technologists, which assist operations under the supervision of surgeons and other surgical personnel, also exhibit a high potential for robotic automation, with 57.1% of their tasks classified as mid-high and 35.7% as high. This reflects the growing use of surgical robots for procedures requiring precision and control, enhancing the capabilities of human surgeons and support personnel.

When comparing the impact of GenAI and AR across these occupations, it becomes evident that certain roles are more suited to GenAI automation, while others may benefit more from robotic technologies. For instance, the text-heavy nature of Medical Transcriptionists makes them prime candidates for GenAI automation, whereas the physical, precision-based tasks of Medical Equipment Preparers are better suited for robotic automation.

9 Classifying occupations by level of potential automatability

To provide a structured understanding of the potential for automation across various health occupations, this study employs a method that classifies detailed occupations (8-digit O*NET-SOC Code) into distinct automatability groups. This classification leverages two critical measures: the weighted average automatability score (μ) and the weighted standard deviation (γ) of task scores at the occupation level. Both measures have been weighted by the relative importance of the underlying tasks, as portrayed in O*NET, to account for the degree of importance of a particular descriptor (task) to the occupation (see Annex C).

The methodology follows the approach developed by the ILO Research Department (2023[17]), offering a view on how susceptible each occupation is to automation by Generative AI (GenAI) or Advanced Robots (AR). In particular, the weighted average automatability score (μ) reflects the mean potential automatability of tasks within an occupation. A higher μ indicates that, on average, the tasks in the occupation are more susceptible to automation (by GenAI, AR or both combined). The weighted standard deviation (γ) measures, instead, the dispersion of automatability scores across different tasks within the same occupation. A higher γ suggests greater variability in the automatability of tasks, indicating that while some tasks may be highly automatable, others may not be as susceptible to automation.

Based on these measures, occupations are classified into four categories: low risk of automation, potential augmentation, potential automation, and high risk of automation. Box 7 describes the categories in detail.

9.1. Occupations potentially exposed to automation using Generative AI

Figure 7 provides a visual representation of health occupations classified by their potential automatability scores using Generative AI (GenAI). The x-axis represents the weighted average potential automatability score, while the y-axis shows the weighted standard deviation. Overall, the results show an average automatability score of 0.34 across occupations, along with occupation-level standard deviations ranging mainly between 0.15 and 0.25. In consequence, the majority of health occupations are classified into the low risk of automation and potential augmentation categories, which suggest that generative AI represents an opportunity to enhance the performance of workers in some specific (mainly cognitive) tasks, instead of a risk of replacement.

Box 7. Classification Framework of Automatability by Occupation

The combination of the average automatability scores (μ) and the standard deviation of the task automatability at the occupation level (γ) is used to classify occupations into four distinct groups:

Low Risk of Automation ($\mu < 0.4$ and $\mu + \gamma < 0.5$)

These occupations have a low average automatability score and low dispersion, indicating that most tasks are not highly automatable. This group represents roles with tasks that require a high degree of human interaction or complex decision-making.

Potential Augmentation ($\mu < 0.4$ and $\mu + \gamma > 0.5$)

Occupations in this category have a modest average automatability score but also a high dispersion, suggesting that some tasks are highly automatable while others are much less so. This indicates a potential for augmentation rather than direct automation where AI and robotic technologies can enhance the performance of human workers in these occupations.

Potential Automation ($\mu > 0.6$ and $\mu - \gamma < 0.5$)

Occupations in this group have a high average automatability score but higher variability across tasks, suggesting that a majority of tasks are highly automatable, but not all. These roles are at a higher risk of being replaced than those in augmentation group, or to be significantly altered by automation technologies.

High Risk of Automation ($\mu > 0.4$ and $\mu - \gamma > 0.5$)

This category includes occupations with high average automatability scores and low dispersion, indicating a uniform high risk of automation across most tasks. These roles are likely to be significantly impacted by automation.

Occupations with an average score between 0.4 and 0.6 were not classified in any of the previous groups to ensure a clear separation between the intermediate groups (potential augmentation and potential automation).

Source: Authors' elaboration based on ILO Research Department (2023[17]), Generative AI and jobs: a global analysis of potential effects on job quantity and quality. https://doi.org/10.54394/FHEM8239.

Low risk of automation

Occupations located in the lower left quadrant of Figure 7, such as Nursing Assistants and Orthodontists, show low potential automatability scores with low standard deviations. These roles involve a high degree of human interaction, complex decision-making, and physical presence, making them less susceptible to automation by generative AI. For instance, Nursing Assistants provide essential patient care services, including bathing, dressing, and feeding patients, tasks that require empathy and adaptability, which are difficult to automate effectively.

Potential augmentation

In the upper left quadrant, occupations such as Physical Therapist Aides and Occupational Therapists exhibit high standard deviations but moderate average scores. The combination of these two indicators (see Box 7) suggests that these roles could see significant benefits from AI augmentation, where AI tools assist rather than replace human workers in their jobs by providing value added in a limited number of tasks, but with high efficacy in them. Physical Therapist Aides, for example, might use AI-driven tools to monitor patient progress and adjust therapy plans in real-time, enhancing the efficiency and effectiveness of their care without replacing the critical human element of patient interaction. In this situation, those occupations are likely to be augmented by AI while many key tasks remain human-centred.

Figure 7. Generative AI automatability score

Note: The shaded area represents occupations with average scores near the 0.5 threshold (ranging from 0.4 to 0.6) and relatively high standard deviations. These occupations are excluded from classification to ensure a clear distinction between the intermediate groups: *potential augmentation* and *potential automation*. The dashed line to the left of the shaded area marks the boundary between *low risk of automation* and *potential augmentation*. Similarly, the dashed line to the right separates *potential automation* from *high risk of automation*.
Source: Authors' calculations based on sequential calls to GPT4 model through the OpenAI API and O*NET data.

Potential Automation

The upper right quadrant includes occupations like Medical and Clinical Laboratory Technologists, which have high automatability scores on average but also high standard deviations. Occupations in this quadrant are exposed to considerable risk of automation as a majority of their tasks could be effectively performed by GenAI. A handful of other tasks, however, are difficult to automate, so automation is likely to lead to significant reshaping of skill demands and tasks for those roles. For instance, Laboratory Technologists who spend a significant amount of time analysing medical samples, a process that can be streamlined with AI algorithms to improve accuracy and speed. AI technologies such as machine learning can analyse complex data sets to identify patterns and make diagnostic recommendations, reducing the manual workload for technologists.

High Risk of Automation

Finally, the lower right quadrant shows occupations with high potential automatability scores and low standard deviations. These roles are highly susceptible to automation because their tasks are well-defined, repetitive, and can be performed by AI with high accuracy. Medical Transcriptionists, for instance, convert audio recordings from health providers into written text, a task that can be effectively automated using GenAI advanced speech recognition technologies. This automation can significantly reduce costs and increase efficiency in health documentation.

9.2. Occupations potentially exposed to automation using advanced robots

Results in Figure 8 analyse the potential for automation by AR. For this technology, the average automatability score across occupations is 0.29 – below that estimated for GenAI – while occupation-level standard deviations range between 0 and 0.3 in most of the cases. Consequently, most occupations fall into the low-risk or potential augmentation categories. Compared to GenAI, AR shows a higher proportion of occupations classified as low-risk, this outcome is influenced by the prevalence of cognitive skills in health-related occupations, which are less suitable to automation by AR. These findings suggest that AR offers opportunities to automate manual and repetitive tasks, enhancing workers' performance without fundamentally altering the nature of their occupations.

Figure 8. Advanced Robotics automatability score

Note: The shaded area represents occupations with average scores near the 0.5 threshold (ranging from 0.4 to 0.6) and relatively high standard deviations. These occupations are excluded from classification to ensure a clear distinction between the intermediate groups: *potential augmentation* and *potential automation*. The dashed line to the left of the shaded area marks the boundary between *low risk of automation* and *potential augmentation*. Similarly, the dashed line to the right separates *potential automation* from *high risk of automation*.
Source: Authors' calculations based on sequential calls to GPT4 model through the OpenAI API and O*NET data.

Low risk of automation

Similar to the findings with GenAI, some health occupations, such as Psychiatrists and Family Medicine Physicians, exhibit low potential automatability scores and low standard deviations also when considering specifically the potential automating capabilities of Advanced Robots. These roles are located in the lower left quadrant, indicating a low risk of automation due to the necessity for intricate human interaction, empathetic communication, and complex decision-making. Also, the fact that most of the tasks of these roles are cognitive in nature, makes it particularly difficult for AR to replace or augment them in the current context.

Potential augmentation

In the upper left quadrant, occupations such as Psychiatric Technicians and Respiratory Therapists show low to moderate automatability scores but higher standard deviations. Results suggest that these positions could benefit from AR augmentation. For example, Respiratory Therapists might use advanced robotic tools to assist in monitoring and adjusting patient ventilation systems, thereby improving the efficiency and effectiveness of respiratory care without replacing the crucial human touch involved in patient interaction. That being said, most of the tasks in this group still cannot be easily automated, so that the impact of AR on these occupations will likely that of augmenting their productivity in a limited set of specific actions and tasks.

Potential automation

Occupations like Medical and Clinical Laboratory Technicians, found in the upper right quadrant, have high potential automatability scores but also high standard deviations. This indicates that, while many tasks could be performed by AR in an effective way, some other are still very difficult to automate. Laboratory Technicians, for instance, can benefit from robotic systems designed to handle high-throughput tasks such as sample preparation and analysis, thereby reducing their manual workload and enhancing accuracy and speed.[13] This not only ensures high accuracy and speed but also frees technicians from repetitive tasks, allowing them to focus on more complex aspects of laboratory work, such as interpreting results and maintaining quality control. Furthermore, automated liquid handling robots can manage tasks such as pipetting, mixing reagents, and setting up assays, which are critical for high-throughput screening and diagnostic testing. These advancements in automation improve laboratory efficiency, reduce the risk of human error, and enable technicians to allocate their expertise to more diagnostic and analytical functions, ultimately enhancing the overall productivity of laboratory operations.

High risk of automation

The lower right quadrant includes roles such as Medical Equipment Preparers and Orderlies, which exhibit high potential automatability scores in conjunction with low standard deviations. These occupations are highly susceptible to automation by AR due to their well-defined, repetitive tasks that robots can perform with increasing degree of precision. For instance, Medical Equipment Preparers can utilise robots for cleaning, sterilising, and preparing medical instruments, streamlining operations and cutting costs. Automated systems efficiently clean and disinfect medical instruments, ensuring compliance with stringent hygiene standards while significantly reducing the time and labour involved in manual cleaning processes. By integrating these robotic systems, health facilities can enhance the turnaround time for medical equipment, improve infection control, and reduce the physical strain on staff responsible for these tasks.

Similarly, Orderlies, who handle routine tasks like patient transport and cleaning, can have many of their duties automated, allowing health staff to focus on more complex, patient-centred activities. Autonomous mobile robots,[14] can navigate hospital corridors to transport medications, linens, and waste, ensuring timely and efficient delivery while minimising the need for human intervention. These robots can also be programmed to assist with patient transport, reducing the physical burden on staff and freeing them up to engage more directly with patient care. By automating these routine tasks, health facilities can optimise their operational efficiency, reduce labour costs, and allow health workers to dedicate more time to tasks that require their clinical expertise and human touch, ultimately enhancing the quality of patient care.

9.3. Combining GenAI and AR scores into one indicator of overall automatability

The analysis of potential automation in health occupations using Generative AI (GenAI) and Advanced Robots (AR) provides distinct insights into how different tasks within an occupation can be automated. However, to create a comprehensive measure of automation potential at the occupation level, it is essential to consolidate these insights into a single indicator. To achieve this goal, it is important to note that different tasks are inherently more suitable for automation using either GenAI or AR based on their nature. For instance, cognitive skills are more amenable to automation using GenAI, whereas physical or manual skills are more likely to be automated using AR. The rationale behind this differentiation is that GenAI excels in tasks requiring data analysis, decision-making, and communication, whereas AR is more effective in tasks involving physical manipulation, movement, and routine manual processes.

To consolidate the automatability scores, therefore, this study classified each task as primarily cognitive or physical/manual using GPT-based analysis. In particular, GPT4 has been interrogated through API on whether any of the 1 600 tasks analysed should be classified as cognitive or physical. This classification guided the identification of the most relevant automation score (either GenAI or AR) to be used in the construction of the final indicator of automation for each task. For instance, tasks such as “Perform health-related tasks, such as monitoring vital signs and medication” were classified as physical/manual and thus aligned with AR automation potential, while tasks like “Provide clients with communication assistance, typing their correspondence or obtaining information for them” were classified as cognitive, aligning with GenAI automation potential. Some examples are provided in Table 1.

Table 1. Example of task classification into cognitive or physical

O*NET-SOC Code	Occupation	Task ID	Task Description	Skill Type
31-1122.00	Personal Care Aides	2369	Perform health-related tasks, such as monitoring vital signs and medication	Physical
		2374	Instruct or advise clients on issues, such as household cleanliness, utilities, hygiene, nutrition	Cognitive
		2370	Administer bedside or personal hygiene assistance	Physical
		2379	Provide clients with communication assistance, typing their correspondence or obtaining information	Cognitive
		2376	Participate in case reviews, consulting with the team, evaluating the client’s needs and plan	Cognitive
		2371	Prepare and maintain records of client progress and services performed	Cognitive
		2373	Care for individuals or families during periods of incapacitation, family disruption, or convalescence	Physical
		2372	Perform housekeeping duties, such as cooking, cleaning, washing clothes or dishes	Physical

Source: Authors’ calculations based on sequential calls to GPT4 model through the OpenAI API and O*NET data.

Once the appropriate score for each task was determined, the study applied the same aggregation method used in earlier sections to compute an overall automation score for the occupation. This involved calculating the weighted average of the task-level scores, with weights corresponding to the importance of each task as provided by O*NET. This approach ensures that the consolidated automation score accurately reflects the varied nature of tasks within an occupation, capturing the full spectrum of automation potential.

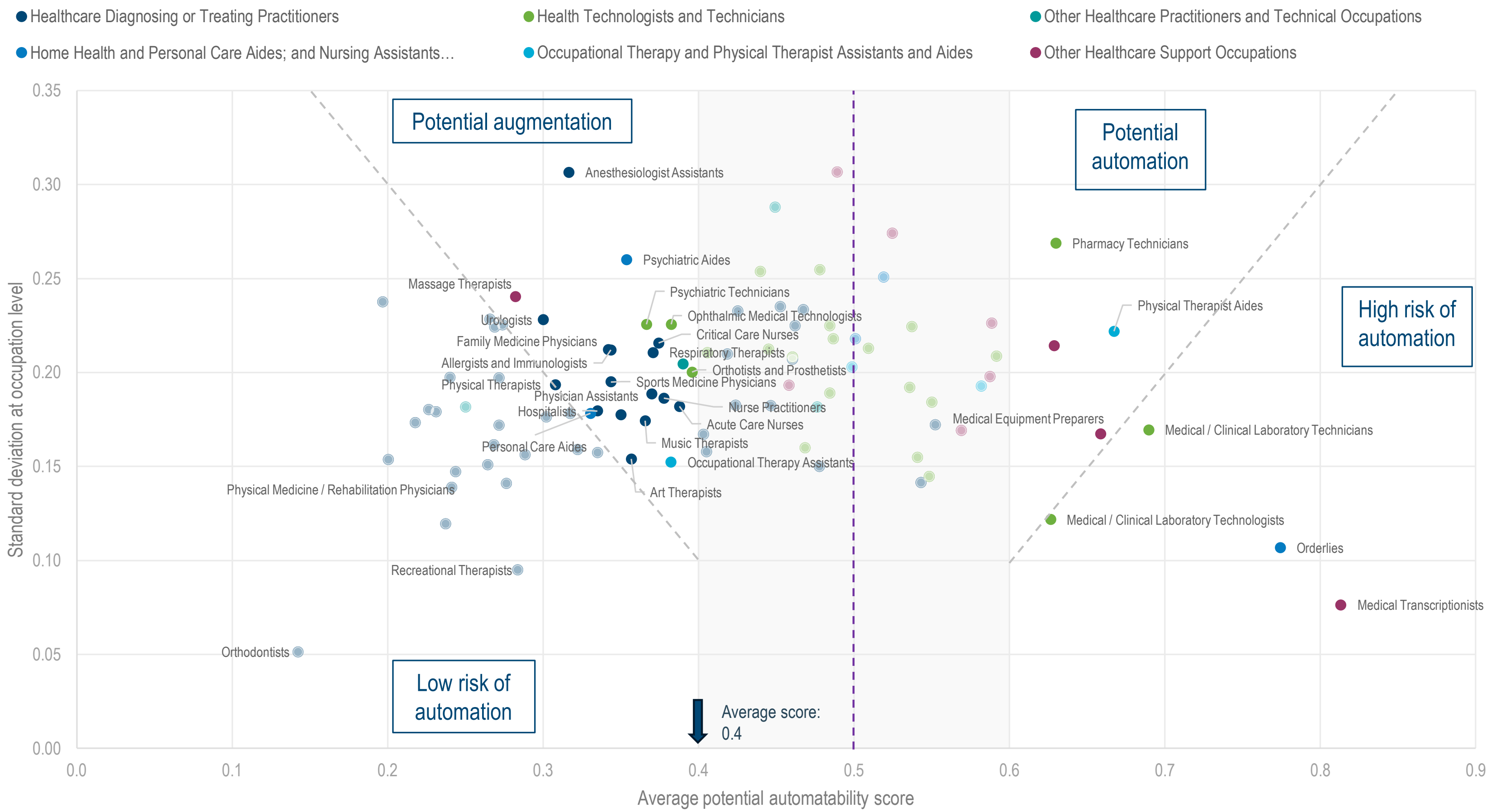
9.4. Overall automatability scores by occupation

The analysis of total automatability scores, which consolidates the potential automation impacts of both Generative AI (GenAI) and Advanced Robots (AR), reveals a distinct distribution of health occupations based on their susceptibility to automation. The results visualised in Figure 9 show that, after considering both technologies, the majority of the occupations fall within the potential augmentation zone or in the intermediate area between 0.4 and 0.6, where occupations are not classified in any specific category. Occupations in this range show both high average scores and variance, and its potential automatability depends on various conditions that could shift them closer to either the potential augmentation or potential automation zones (International Labour Organization. Research Department., 2023[17]). This outcome aligns with the still-emerging nature of Artificial Intelligence and the persistent challenges of integrating AI into robotic systems, highlighting the complexities involved in developing the full potential of these technologies.

9.4.1. Low risk of automation

Family Medicine Physicians, for instance, diagnose and treat a wide range of ailments, requiring nuanced judgment and personalised patient care. The interpersonal skills and comprehensive medical knowledge needed are difficult for AI and robots to replicate. Similarly, Orthodontists design and apply orthodontic appliances, requiring precise manual dexterity and patient-specific adjustments that are not easily automated.

Figure 9. Overall automatability scores by occupations



Note: The shaded area represents occupations with average scores near the 0.5 threshold (ranging from 0.4 to 0.6) and relatively high standard deviations. These occupations are excluded from classification to ensure a clear distinction between the intermediate groups: *potential augmentation* and *potential automation*. The dashed line to the left of the shaded area marks the boundary between *low risk of automation* and *potential augmentation*. Similarly, the dashed line to the right separates *potential automation* from *high risk of automation*.
Source: Authors' calculations based on sequential calls to GPT4 model through the OpenAI API and O*NET data.

Potential augmentation

Occupations classified can significantly benefit from automation technologies augmenting human capabilities, enhancing efficiency and effectiveness without fully replacing human workers. Anaesthesiologist Assistants, in this group, can benefit from robotic systems that monitor vital signs and administer anaesthesia under the supervision of anaesthesiologists, reducing the workload and increasing precision. Physical Therapists can also benefit from advancements in robotics that can assist them with repetitive tasks such as guided exercises, allowing therapists to focus on developing personalised treatment plans and providing hands-on care where needed.

Potential automation

Occupations in the Potential Automation group include Medical Equipment Preparers who can utilise robotic systems for cleaning, sterilising, and preparing medical instruments, which streamlines operations and ensures high standards of hygiene and efficiency. Technologies like robotic sterilisation systems and automated inventory management are key enablers. Pharmacy Technicians can also leverage automated dispensing systems and robotic prescription processing which can handle routine tasks such as filling prescriptions and managing inventory, allowing technicians to focus on customer service and complex medication management tasks.

High risk of automation

Occupations in the High Risk of Automation group often involve repetitive, standardised processes that are well-suited to automation. Several of the tasks of current Medical Transcriptionists, for instance, could be automated by AI-powered speech recognition software that can transcribe medical reports with high accuracy, drastically reducing the need for human transcriptionists. Technologies like Nuance Dragon Medical One are already in use, transforming the way medical documentation is handled. Some of the typical tasks of Orderlies can also be automated by robots designed for logistics and patient transport. These robots can take over many routine tasks performed by orderlies, such as moving patients between rooms and delivering supplies.

10 Estimating the share of health employment exposed to augmentation and automation from GenAI and AR

To assess the share of employment exposed to augmentation or automation in the health sector, the analysis leverages employment estimates by occupation available at the SOC (Standard Occupational Classification) 6-digit level. The methodology involves aggregating task-level automatability scores, previously calculated at the 8-digit level, to the 6-digit level, thereby aligning with the granularity of employment data. This aggregation allows for a comprehensive understanding of the potential impact of automation and augmentation on health occupations.

Each occupation is assessed based on the weighted average of task-level scores for both GenAI and AR technologies (overall automatability score). The results, as shown in Table 2, indicate significant variations in the potential for automation and augmentation across health occupations. The analysis reveals that a substantial portion of the health workforce is likely to experience changes due to automation and augmentation technologies, with potential impacts on employment figures and shares.

The potential augmentation category includes 16 occupations that collectively account for 31% of health employment in the United States in 2022, translating to approximately 4 949 700 workers. Registered Nurses dominate this group with 3 172 500 employees, representing 19.8% of the total health workforce. Other significant occupations in this category include Physician Assistants (148 000 workers) and Respiratory Therapists (133 100 workers). These roles involve tasks that can be enhanced through the use of advanced technologies, allowing professionals to focus on more complex, patient-centred activities.

The potential automation category, instead, includes four occupations, representing approximately 3.6% of total health employment, or about 570 800 workers. Pharmacy Technicians and Physical Therapist Aides are notable examples in this group, with employment figures of 459 600 and 44 500 respectively. The tasks in these roles are more routine and repetitive, making them suitable for automation, which can improve efficiency and reduce errors.

Finally, the high automation risk category comprises two occupations, Orderlies and Medical Transcriptionists, representing a much smaller share of employment, around 0.6% of the total health workforce, or approximately 94 500 workers. The tasks in these occupations are highly susceptible to automation due to their routine and repetitive nature. For example, AR can perform tasks such as patient transport and data entry, allowing health staff to focus on more critical aspects of patient care.

Table 2. Employment figures by automation category

United States, health occupations

SOC 6-digit Code	Occupation	Employment 2022 (thousands)	Share health (%)
Potential Augmentation			
29-1071	Physician assistants	148	0.9
29-1122	Occupational therapists	139.6	0.9
29-1123	Physical therapists	246.8	1.5
29-1126	Respiratory therapists	133.1	0.8
29-1129	Therapists, all other	103.3	0.6
29-1141	Registered nurses	3 172.5	19.8
29-1171	Nurse practitioners	266.3	1.7
29-1215	Family medicine physicians	108	0.7
29-1229	Physicians, all other	330.9	2.1
29-2053	Psychiatric technicians	107.1	0.7
29-2091	Orthotists and prosthetists	9.5	0.1
29-9091	Athletic trainers	33.8	0.2
31-1133	Psychiatric aides	32.4	0.2
31-2011	Occupational therapy assistants	53.1	0.3
31-9011	Massage therapists	134.3	0.8
TOTAL		**4 949.7**	**30.9**
Potential Automation			
29-2052	Pharmacy technicians	459.6	2.9
31-2022	Physical therapist aides	44.5	0.3
31-9093	Medical equipment preparers	99.6	0.6
TOTAL		**570.8**	**3.6**
High Risk of Automation			
31-1132	Orderlies	45.5	0.3
31-9094	Medical transcriptionists	49	0.3
TOTAL		**94.5**	**0.6**

Source: Authors' calculations based on U.S. Bureau of Labor Statistics (2022[19]) and sequential calls through OpenAI's GPT4 model.

10.1. A discussion of the challenges and opportunities posed by the integration of GenAI and AR into health

The results of the analysis above bear several key policy implications as this study shows there are substantial potential gains from automation in the health sector but, also, potential challenges.

One important message stemming from the results relates the necessity to invest in continuous education and training programmes to help health professionals adapt to new technologies. For occupations with high potential for augmentation, such as Registered Nurses and Physician Assistants, for instance, training programmes should focus on enhancing digital literacy and competencies related to advanced medical technologies. By providing these professionals with the necessary skills, they could leverage technology to improve patient outcomes and streamline clinical workflows (see Box 8).

Box 8. Supporting the adoption of digital technologies in Nursing and Physician Assistant activities

For occupations with high potential for augmentation, such as Registered Nurses and Physician Assistants, training programmes could focus on enhancing digital literacy and competencies related to advanced medical technologies. these professionals should be trained in the use of electronic health record (EHR) systems. These systems are crucial for managing patient information, streamlining communication between health providers, and ensuring accurate and up-to-date patient records. Understanding how to navigate and utilise EHR systems effectively can significantly improve the efficiency of patient care and reduce the likelihood of errors.

Additionally, training should encompass familiarity with telemedicine platforms, which have become increasingly important, especially in the context of the COVID-19 pandemic. Platforms that enable health providers to offer remote consultations, thus expanding access to care and reducing the burden on physical health facilities are likely to become a key component of future health systems and proficiency in telemedicine tools can enhance a nurse's or physician assistant's ability to provide timely and effective care to patients in remote or underserved areas.

Knowledge of wearable health technology is also becoming essential. These devices collect real-time health data such as heart rate, activity levels, and sleep patterns, which can be integrated into patient care plans to monitor chronic conditions or track recovery progress. Training in interpreting and utilising data from these wearables can provide health professionals with a more comprehensive understanding of a patient's health, allowing for more personalised and proactive care.

Secondly, for occupations identified as having a high risk of automation, such as Orderlies and Medical Transcriptionists, policies should encourage the integration of automation technologies while minimising displacement and enhancing, instead, career mobility. Automation can significantly improve efficiency and accuracy in routine tasks, which can free up health workers to focus on more complex and patient-centred activities. For example, robotic systems can handle tasks like cleaning and sterilising medical equipment or transporting patients, reducing the manual workload on staff. Effective integration of automation can lead to significant improvements in efficiency and accuracy, but it is crucial to ensure that displaced workers are given opportunities to reskill and transition into new roles within the health sector and/or that occupational skill demands evolve with the adoption of new technologies so that these can also be integrated in life-long learning. Policymakers must also create pathways for workers exposed to high risk of automation to acquire new skills that are in demand, thereby reducing the negative impact of automation on employment.

On top of the challenges related to effective training, the integration of advanced technologies such as AI and robotics into health practices raises ethical and regulatory considerations. Policymakers must establish clear guidelines and standards for the use of these technologies to protect patient privacy and ensure the ethical use of AI in clinical decision-making. By addressing these challenges through comprehensive and forward-thinking policies, the health sector can maximise the benefits of automation and augmentation while minimising the potential downsides.

The transition towards the adoption of AI, Advanced Robotics and digital skills requires effective efforts to ensure that training is available. Understanding what occupations are most susceptible to automation and augmentation allows for the development of strategies to optimise workforce deployment, enhance patient care, and ensure that health systems are resilient to future technological advancements. This involves not only investing in technology but also in the human capital necessary to manage and operate these new systems. For example, training programmes for health IT professionals can be expanded to include advanced data management and cybersecurity skills, ensuring that the digital infrastructure supporting automated systems is robust and secure.

While the path to the adoption of AI and robotics into health presents challenges, it is important to note that automation can address critical labour shortages which have been a persistent bottleneck in the health sector across countries. By automating routine and administrative tasks, health professionals can dedicate more time to direct patient care. This can improve patient outcomes and increase job satisfaction among health workers.

11 Conclusions

The analysis presented in this paper provides an examination of the evolving landscape of digital and AI-related skills in the health sector across Canada, the United Kingdom and the United States. This study leverages data from millions of online job postings to track the evolution of the demand for digital competencies, including GenAI and those related to the interaction with Advanced Robots, and their integration into various health occupations.

The study highlights a variety of key results. Results for the United States, for instance, show that its health sector exhibits a significant demand for digital skills, particularly in areas such as Health Information Management/Medical Records, Computer Science, and Data Analysis. The steady increase in job postings mentioning these skills underscores the sector's shift towards digital health technologies. Results suggest that electronic health records (EHRs) have become essential for managing patient data, enhancing care co-ordination, and improving clinical outcomes. The adoption of AI in niche roles, such as AI-driven diagnostic tools in radiology, also highlights the transformative potential of these technologies.

In the United Kingdom, the demand for digital skills like Cybersecurity, Data Analysis, and Clinical Informatics reflects the health sector's commitment to integrating advanced technologies to improve patient care and operational efficiency. The rise in cybersecurity skills indicates a heightened focus on protecting patient data amidst increasing digitisation. Similarly, the demand for clinical informatics skills emphasises the importance of managing and analysing clinical data to support decision-making processes.

Canada shows a more stable (yet growing) demand for digital skills in health occupations, with a notable emphasis on Health Information Management/Medical Records, Computer Science, and Data Analysis. The regional approach to digital health integration highlights the varying levels of digital maturity across provinces. The increased demand for data collection and clinical informatics skills points to the sector's focus on leveraging data for improving health services.

While the volume of job postings for AI developers in health occupations is rather small (though increasing), the way AI is likely to impact the health sector can go through its adoption in the workplace through the adoption of technologies in ordinary tasks.

The study identifies several health occupations with high potential for augmentation and automation through AI and the use of Advanced Robots. It does so by analysing tasks requirements at the occupational level in the United States. For instance, some of the tasks of Registered Nurses and Physician Assistants likely to be augmented by AI and AR, increasing productivity and the efficacy with which these professionals can deliver health. In turn, these roles could benefit from enhanced digital literacy and competencies related to advanced medical technologies, such as AI-powered diagnostic tools and telehealth platforms.

On the other hand, roles like Medical Equipment Preparers and Orderlies are more likely to experience significant automation, posing some challenges as to how these automating technologies could replace humans in the workplace. Robotic systems, for instance, can handle tasks such as cleaning, sterilising, and preparing medical instruments, thereby reducing manual workload and enhancing operational efficiency. These technologies enable health staff to focus on more complex, patient-centred activities, improving overall health delivery, but the steady advancement in AI and AR is poised to lead to further automation in the future which could lead to significant impacts on employment prospects of workers in those roles. The findings of this study underscore the necessity for targeted policy interventions to facilitate the digital transformation of the health workforce.

Firstly, investment in training and education is paramount. For occupations with high potential for augmentation, such as Registered Nurses and Physician Assistants, training programmes should focus on enhancing digital literacy and competencies related to advanced medical technologies. For instance, professionals should be familiar with AI-powered diagnostic tools and telehealth platforms, which are becoming integral to modern health delivery.

Secondly, if the digital transition and the adoption of new AI technologies has to benefit everyone, policymakers must address the digital divide by providing resources and support to underserved areas, ensuring that all health providers can leverage the benefits of digital and AI technologies. This includes investing in digital infrastructure and providing training for health workers in areas where connectivity and digitalisation and the digital literacy may still be relatively low.

Lastly, data privacy and security must also be a priority. As health systems increasingly rely on digital tools, robust data governance frameworks are essential to protect patient information and maintain public trust. Policies should promote the secure use of health data, ensuring compliance with regulations while enabling the effective use of AI and digital technologies.

This study shows how the integration of digital and AI skills in the health sector presents both opportunities and challenges and provides details about both aspects. By fostering a digitally skilled workforce, ensuring equitable access to technologies, and prioritising data privacy, policymakers can enhance the efficiency, quality, and accessibility of health services.

Notes

[1] These roles encompass jobs that are not directly involved in patient care or clinical support but are essential for the operation of healthcare facilities. Examples include data analysts, administrative staff, finance professionals, etc. These positions are advertised for recruitment in hospitals and other health settings but do not require clinical qualifications.

[2] Notice that GenAI is part of the broader AI field and, unless otherwise stated, this paper refers to the latter. However, the analysis of the potential impact of automation focuses specifically on Generative AI (GenAI) rather than the broader field of Artificial Intelligence (AI) due to its broader potential reach to workers not directly involved in AI development.

[3] Orderlies "[t]ransport patients to areas such as operating rooms or x-ray rooms […], maintain stocks of supplies or clean and transport equipment". It excludes Nursing Assistants. Medical Transcriptionists "[t]ranscribe medical reports recorded by physicians and other healthcare practitioners…" (National Center for O*NET Development, 2024[23]; U.S Bureau of Labor Statistics, 2024[24]).

[4] Note for instance the OECD Recommendation on Health Data Governance that recognises how 'personal health data, being sensitive in nature and subject to ethical standards and the principle of medical confidentiality, require a particularly high level of protection and that technological developments can both enable the privacy protective use of personal health data and also introduce new risks to privacy and data security'.

[5] Other OECD work analyses data using online job postings from different sources. The OECD AI observatory, for instance, presents detailed information on trends in the demand and supply of AI talent across countries and sectors over time using data coming from LinkedIn and Adzuna.

[6] By using 2 digital skills as a threshold, some job postings mentioning only one broadly used skill (i.e. Excel, Word, etc.) are filtered out of the final selection.

[7] More detailed examples by occupation and country are also provided in 11Annex B.

[8] The ten most mentioned skills were defined according to the annual average mentions between 2018 and 2023.

[9] As well as the role of Generative AI, as a particular field of it, see Box 6.

[10] It is important to note that this section of the paper looks into the potential automation impact of GenAI rather than AI more broadly. More details about the difference between the two concepts and the reason why GenAI is analysed are given in Box 6.

[11] Medical Transcriptionists (SOC: 31-9094), "transcribe medical reports recorded by physicians and other healthcare practitioners using various electronic devices, covering office visits, emergency room visits, diagnostic imaging studies, operations, chart reviews, and final summaries. Transcribe dictated reports and translate abbreviations into fully understandable form".

[12] Orderlies (SOC: 31-1132) "Transport patients to areas such as operating rooms or x-ray rooms using wheelchairs, stretchers, or moveable beds. May maintain stocks of supplies or clean and transport equipment. Psychiatric orderlies are included in Psychiatric Aides". See www.onetonline.org/link/summary/31-1132.00.

[13] For example, robotic systems like the Cobas® 8800 from Roche automate the entire process of sample testing, from loading samples to generating results https://diagnostics.roche.com/global/en/products/instruments/cobas-8800-ins-2694.html.

[14] See for instance the TUG from Aethon.

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Annex A. Data and methodology used to track the demand for digital and AI skills in health occupations and in the sector

Data from online job postings offer several advantages over traditional labour market data. For instance, unlike traditional labour market statistics, online job postings offer rich, timely, and detailed data. They provide up-to-date insights into employers' evolving skill demands and can identify new and emerging trends as they happen. This real-time data collection allows for the analysis of changes in skill requirements across different regions and occupations, offering a nuanced view of the labour market's shifting landscape.

While the use of big data has several advantages, there are also limitations to using job postings data. Not all job openings are advertised online, as some recruitment occurs through informal networks or word-of-mouth. This limitation may disproportionately affect certain industries and occupations. For example, industries that predominantly require high-skilled workers may be overrepresented in online data, as suggested by comparisons with official statistics (Carnevale, Jayasundera and Repnikov, 2014[20]; Tsvetkova et al., 2024[21]). Specifically, occupational groups like Business, Finance, and Administration and Management tend to be overrepresented in these datasets. Consequently, AI-related job postings might also be somewhat overrepresented, given their typically high skill level and likelihood of being advertised online. Similarly, another limitation comes as OJPs capture new demand published online. This can reflect increase demand in the labour market as well as churn being the two are difficult to disentangle.

The health occupations analysed in this paper and the taxonomies used

The empirical analysis in this study leverages the Lightcast® Occupation Taxonomy (LOT) and the North American Industry Classification System (NAICS) classification available in Lightcast databases. Job postings were categorised into two primary groups: Health Occupations and Other Occupations in the Health Sector:

Health occupations

This category encompasses all job postings classified under the career area code 20 – Healthcare within the LOT framework. The relevant level of disaggregation for this group is the occupation group (LOT 4-digit code). This category includes a range of professions devoted to health-related services, demanding both technical healthcare and patient-centred skills, including 28 occupation groups such as (quoted definitions taken from LOT (Lightcast, 2024[22]):

- Physicians: "Diagnoses and treats illness and injuries in patients. May specialise in working with a particular group of people (such as children), or a particular area of healthcare".
- Registered/Practical Nursing: "Provides medical care and treatment, educates patients about their conditions, and provides emotional support to patients and families".

- Health IT Professionals: Specialists responsible for the management and implementation of health information systems and technologies. It includes occupations such as Clinical Data Analysts, Healthcare Analysts, Clinical Data Developer and Electronic Medical Records Specialists.
- Patient Care Technicians: Health workers who provide direct patient care and assist with medical procedures. It includes occupations such as Medical Assistants, Phlebotomists, Dialysis Technicians and Endoscopy Technicians.

Other occupations in the health sector

This category comprises all job postings classified under NAICS code 63 – Health industry, excluding those classified in the LOT code 20 – healthcare. This group includes all job postings that are not directly involved in patient care or clinical support but are essential for the operation of healthcare facilities. The relevant level of disaggregation for this group is also the occupation group (LOT 4-digit code). Representative examples of occupations within this group include:

- Data Analysts and Mathematicians: Professionals who analyse health data to enhance decision-making and operational efficiency.
- Business Intelligence Experts: Specialists who develop strategies based on data insights to improve health services and organisational performance.
- Software Engineers: Engineers responsible for designing and maintaining software systems used in health settings.

The analysis in this paper keeps these two groups separate to discern the distinct skill sets and demands associated with each category. Health occupations primarily require clinical and medical skills, along with an increasing need for digital proficiency driven by advancements in health technologies. In contrast, other occupations in the health sector necessitate specialised skills in data analysis, software development, and business intelligence.

Identification of digital skills from online job postings

The Lightcast® skill taxonomy organises skills into 31 categories and over 440 subcategories.[1] For the purposes of this study, the analysis concentrated on four categories encompassing IT, digital, and technology skills, ensuring a targeted examination of the relevant competencies. The categories are Analysis, Engineering, Information Technology and Science and Research.

A total of 90 subcategories were selected based on their relevance for this study (see Table A A.1). For instance, within the 'Engineering' category, subcategories such as Robotics and Optical Engineering were retained. This selective approach ensured a focus on skills directly applicable to health technology and digital advancements rather than all digital skills.

In addition, given the study's emphasis on health, a subset of three subcategories (of a total of 56) from the Health Care skill category was also included:

- Clinical Informatics: Includes skills such as clinical decision support, dental informatics, imaging informatics, among others.
- Health Information Management and Medical Records: Includes clinical data exchange, patient data management systems, electronic medical records, etc.
- Medical Equipment and Technology: Includes medical software, DaVinci surgical systems, patient monitoring systems, etc.

With the resulting skills contained in the selected subcategories, a classification rule was applied that consists of selecting those new job advertisements where at least 2 digital skills are mentioned by employers in the job description.

Table A A.1. Categories and subcategories of skills used for classifying digital job postings

SKILL CATEGORY	SKILL SUBCATEGORY	COUNT SKILLS
Analysis	Business Intelligence	34
	Business Intelligence Software	73
	Data Analysis	105
	Data Science	128
	Data Visualization	53
	Image Analysis	34
	Mathematical Software	11
	Natural Language Processing (NLP)	46
	Statistical Software	25
Engineering	Automation Engineering	69
	Engineering Software	85
	Robotics	19
	Signal Processing	38
	Simulation and Simulation Software	59
Information Technology	Agile Software Development	33
	Application Programming Interface (API)	82
	Artificial Intelligence and Machine Learning (AI/ML)	153
	Augmented and Virtual Reality (AR/VR)	23
	Backup Software	38
	Blockchain	19
	C and C++	27
	Cloud Computing	42
	Cloud Solutions	138
	Collaborative Software	27
	Computer Hardware	122
	Computer Science	150
	Configuration Management	32
	Content Management Systems	37
	Cybersecurity	293
	Data Collection	16
	Data Management	125
	Data Storage	109
	Database Architecture and Administration	102
	Databases	162
	Distributed Computing	39
	Enterprise Application Management	57
	Enterprise Information Management	34
	Extensible Languages and XML	50
	Extraction, Transformation, and Loading (ETL)	29
	Firmware	10
	General Networking	170
	Geospatial Information and Technology	87
	Identity and Access Management	78
	Integrated Development Environments (IDEs)	35
	Internet of Things (IoT)	17
	iOS Development	24

SKILL CATEGORY	SKILL SUBCATEGORY	COUNT SKILLS
	IT Automation	71
	IT Management	79
	Java	102
	JavaScript and jQuery	91
	Log Management	27
	Mainframe Technologies	31
	Malware Protection	24
	Microsoft Development Tools	61
	Microsoft Windows	55
	Middleware	37
	Mobile Development	50
	Network Protocols	145
	Network Security	113
	Networking Hardware	49
	Networking Software	43
	Operating Systems	105
	Other Programming Languages	100
	Query Languages	35
	Scripting	36
	Scripting Languages	54
	Search Engines	15
	Servers	103
	Software Development	342
	Software Development Tools	303
	Software Quality Assurance	171
	System Design and Implementation	98
	Systems Administration	119
	Technical Support and Services	76
	Telecommunications	163
	Test Automation	85
	Version Control	33
	Video and Web Conferencing	22
	Virtualization and Virtual Machines	99
	Web Content	25
	Web Design and Development	175
	Web Services	36
	Wireless Technologies	47
Science and Research	Bioinformatics	24
	Biotechnology	9*
	Genetics	62*
	Science Software	36
Health Care	Clinical Informatics	19
	Health Information Management and Medical Records	63
	Medical Equipment and Technology	13
TOTAL		6 585

Note: Skill categories, subcategories and skills can be explored in https://lightcast.io/open-skills/categories. Please consider that the taxonomy receives regular updates, then numbers can vary. * For the subcategories Biotechnology and Genetics only a subset of the skills were considered for the classification.
Source: OECD based on Lightcast Skills Taxonomy.

Identification of AI-related skills from online job postings

To identify AI-related skills and job postings in the health sector, the study employed a comprehensive methodology using the Lightcast skill taxonomy. In particular, the approach involved the extraction and classification of AI-related job postings based on a detailed list of AI-related keywords. The list of keywords, which includes 309 distinct skills grouped into seven clusters, was derived from existing literature (Borgonovi et al., 2023[13]) and supplemented with additional terms identified during the data analysis process.

The AI-related skills were categorised into seven clusters, each representing a specific domain of AI applications. This structured approach ensured that the analysis captured the diverse range of competencies required in the health sector. The clusters and some of their representative skills are:

- **Artificial Intelligence Systems**: Includes different types of AI-powered systems, in particular 43 skills such as Artificial Intelligence Systems, Azure Cognitive Services, Baidu, Cognitive Automation, Cognitive Computing, Computational Intelligence, Cortana, and Expert Systems. These skills encompass the foundational elements of AI systems and their application in various health contexts.
- **Autonomous Driving:** Comprises 16 skills related to the development of vehicles operating and navigating without human intervention. This cluster includes terms like Autonomous Systems, Autonomous Vehicles, Guidance Navigation and Control Systems, Light Detection and Ranging (LiDAR), OpenCV, Path Analysis, Path Finding, and Remote Sensing. Although primarily associated with transportation, these skills are increasingly relevant in medical robotics and automated health delivery systems.
- **Machine Learning:** Includes 95 skills enabling machines to learn from experience without explicit programming to make predictions based on identified patterns. It covers a broad spectrum of machine learning techniques and tools, including Apache Spark, Association Rule Learning, Automated Machine Learning, Decision Models, Decision Tree Learning, Dimensionality Reduction, Markov Chain, Matrix Factorization, and Meta Learning. These skills are critical for developing predictive models and enhancing diagnostic accuracy in health.
- **Natural Language Processing (NLP):** Contains 72 skills dealing with the interaction between computers and human language. Key skills include Hugging Face Transformers, Intelligent Agent, Intelligent Software Assistant, Semantic Search, Sentiment Analysis, Seq2Seq, Word Embedding, and Word2Vec Models. NLP is pivotal in processing and interpreting vast amounts of unstructured medical data.
- **Neural Networks:** It is a type of machine learning models inspired by the structure of the human brain. Comprising 23 skills, this cluster includes Chainer (Deep Learning Framework), Convolutional Neural Networks, Cudnn, Deep Learning, Deeplearning4j, Keras (Neural Network Library), and Long Short-Term Memory (LSTM). These skills are essential for developing complex AI models capable of handling intricate medical datasets.
- **Robotics:** With 21 skills, the robotics cluster includes skill used on the design and construction of devices that can (semi-)autonomously perform physical tasks, such as Motion Planning, Nvidia Jetson, Robot Framework, Robot Operating Systems, and Robotic Liquid Handling Systems. These skills are vital for the implementation of robotic systems in surgical procedures, automated laboratory processes, and patient care.
- **Visual Image Recognition:** This cluster refers to the use of algorithms to analyse and interpret visual data, such as images or videos. Containing 39 skills, it encompasses Image Segmentation, Image Sensor, Imagenet, Motion Analysis, Realsense, Variational Autoencoders, and Object Detection. Visual image recognition is crucial for medical imaging, enabling more accurate and efficient diagnostic processes.

In the list, each AI skill was classified as generic or specific. Generic skills refer to those AI skills that can be common in roles using AI systems but not necessarily developing them. These include, for instance, *machine learning*, *applications of artificial intelligence* or *sentiment analysis*. In contrast, specific skills include AI skills related with more specific applications or methods, such as *gaussian process*, *transformers* or *Apache Spark*. This document considers a job posting as AI-related if it includes at least one specific or two generic AI skills.

Note

[1] "Subcategories are groups of skills specific to performing a particular aspect of a job (e.g. Subcategories are developed using a combination of statistical clustering methodologies and curatorial review by domain experts. Skills. Skills are the basic unit of classification in our taxonomy" (see https://lightcast.io/our-taxonomies).

Annex B. Digital and AI skills in healthcare: Illustrative occupational demands

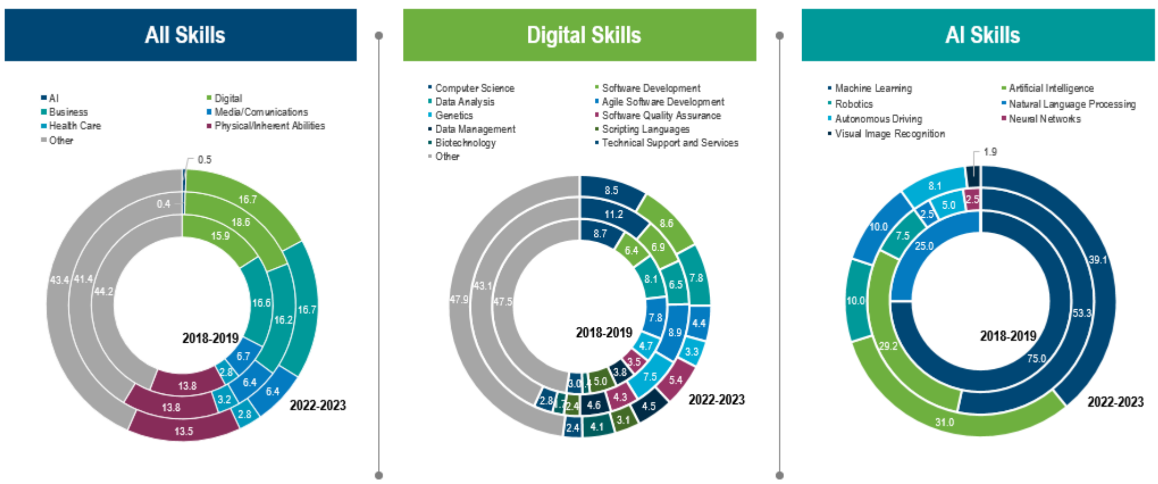
The rapid expansion and recent developments of digital and AI technologies has the potential to bring profound changes in occupational skill demands in the health sector. This section examines specific examples of digital-related occupations across different countries, providing a comprehensive characterisation of some of these evolving skill requirements. This Annex delves into analysis of the combination and mix of different skill set with the purpose of illustrating examples of technology adoption, provides insights into the specific skill demands in a selection of occupations and examples of technologies that are currently being adopted in health practices.

Canada: Clinical research occupations

The analysis of skill demands within the OJPs seeking to hire Clinical Research professionals in Canada reveals significant trends in the importance of digital and AI competencies.

Panel A in Figure A B.1 presents the share of various selected skill categories (ranging from digital to business and media) out of the total skill mentions for Clinical Research occupations in Canada. The demand for digital skills stands out, making up 16.7% of the total skill mentions in 2022-23 in job postings seeking to hire professionals in Clinical Research roles. The demand for digital skills reflects the necessity for clinical researchers to handle complex data sets, use advanced software tools, and integrate technology into their research methodologies. For example, digital tools such as EDC (Electronic Data Capture) systems are essential for managing electronic health records. These tools streamline data collection and analysis processes, ultimately improving research efficiency and accuracy.

Figure A B.1. Clinical research occupations: A characterisation of the skill demand in Canada



Source: OECD based on Lightcast data.

Business skills also hold a significant share of the total skill demand for the occupation, summing up to around 16-17% of total skill mentions across the years examined in this study. Business skills[1] are crucial for the effective management and co-ordination of research projects. Project management, budgeting, and organisational skills enable researchers to handle multiple projects, secure funding, and ensure that research activities comply with regulatory standards. Effective business skills can lead to more successful research outcomes, as they help in planning, executing, and monitoring research projects systematically.

AI skills, though representing a much smaller portion of the total skill mentions (0.5% in 2022-23), have shown a notable increase in demand, reflecting the growing role of artificial intelligence in clinical research. AI technologies can enhance data analysis, automate repetitive tasks, and uncover patterns in data that may not be visible through traditional analysis methods. The integration of AI in clinical research is transforming the field, allowing for more sophisticated and efficient research processes.

Figure A B.1. Panel B proposes a fine-grained breakdown of the digital competencies demanded within Clinical Research occupations. Computer Science skills, making up 8.5% of the skill mentions in 2022-23, are essential for developing algorithms, managing databases, and ensuring the secure handling of sensitive data. Results also show that the demand for Software Development skills has increased to 8.6%, indicating a need for professionals who can create and maintain research-specific software tools.

Data Analysis skills, accounting for 7.8% of the digital skill mentions, are critical for interpreting large volumes of research data. Effective data analysis enables researchers to derive meaningful insights from their data, supporting evidence-based conclusions and enhancing the validity of their research findings. Advanced data analysis techniques are increasingly important in clinical research for identifying trends and making informed decisions and extensively used for statistical modelling and predictive analytics, essential for clinical trial analysis.

Finally, Figure A B.1. Panel C highlights the specific AI competencies sought within Clinical Research occupations. Machine Learning dominates the AI skill demands, accounting for 39.1% of the total AI skill mentions in 2022-23. Machine learning algorithms can process vast amounts of data and identify patterns that would be difficult to detect with traditional statistics. In clinical research, these algorithms can predict patient outcomes, optimise treatment plans, and personalise patient care based on individual data. For instance, machine learning models can analyse patient data to identify risk factors for diseases, enabling early intervention and personalised treatment strategies.

Artificial Intelligence skills are also significant, making up 31.0% of the AI skill mentions. AI technologies can automate data analysis, enhance the accuracy of diagnostic tools, and facilitate the development of new medical treatments. AI-driven tools like those from DeepMind Health[2] can analyse medical images to detect anomalies, providing valuable support to researchers in diagnosing and treating diseases. These tools leverage deep learning algorithms to interpret complex medical images with high accuracy, aiding in faster and more accurate diagnoses.

Natural Language Processing (NLP) skills, representing 10.0% of the AI skill mentions, are essential for analysing textual data. NLP techniques can help extract valuable information from medical records, research articles, and patient feedback, enabling researchers to incorporate diverse data sources into their studies. This capability is particularly useful for systematic reviews and meta-analyses, where large volumes of text need to be processed and analysed.

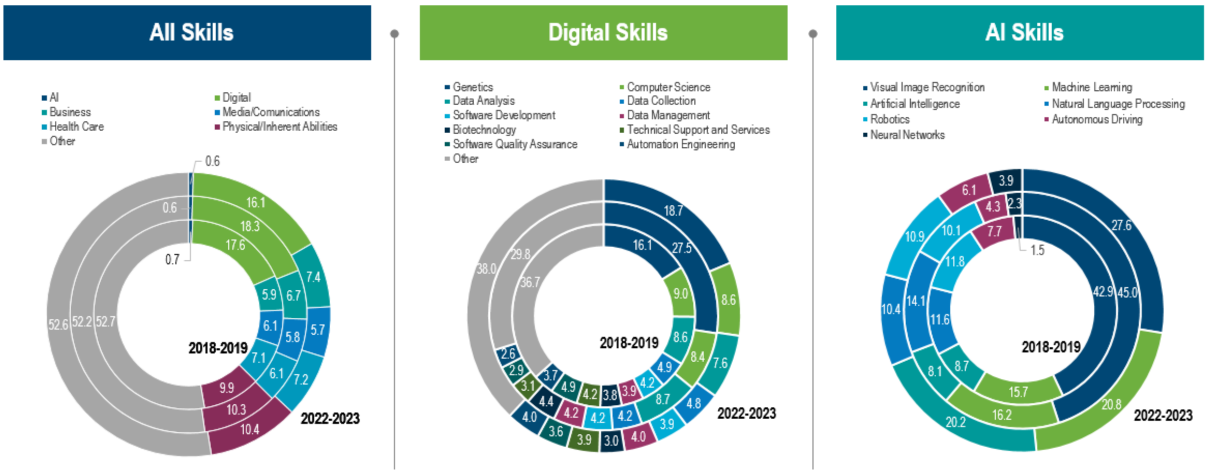
United Kingdom: Clinical laboratory technologists and technicians

The analysis of skill demands within Clinical Laboratory Technologists and Technicians roles in the United Kingdom reveals a clear trend towards the increasing integration of digital and AI competencies.

Figure A B.2 Panel A presents the share of various skill types out of the total skill mentions for Clinical Laboratory Technologists and Technicians in the United Kingdom. Digital skills stand out with a substantial share, making up 16.1% of the total skill mentions in 2022-23. This result indicates the growing importance of technological competencies in clinical laboratory work. The demand for digital skills reflects the necessity for laboratory technologists and technicians to handle complex data sets, use advanced software tools, and integrate technology into their methodologies. For example, digital tools such as LabWare LIMS (Laboratory Information Management System) are essential for managing sample data and laboratory workflows. These tools streamline data collection and analysis processes, ultimately improving laboratory efficiency and accuracy.

Business skills also hold a significant share of the total skill demand for the occupation, increasing to 7.4% in 2022-23. Business skills are crucial for the effective management and co-ordination of laboratory operations. Project management, budgeting, and organisational skills enable technologists and technicians to handle multiple projects, secure funding, and ensure that laboratory activities comply with regulatory standards. Effective business skills can lead to more successful laboratory outcomes by aiding in the planning, execution, and monitoring of laboratory processes systematically.

Figure A B.2. Clinical Laboratory Technologists: A characterisation of the skill demand in the United Kingdom



Source: OECD based on Lightcast data.

Zooming in, Figure A B.2 Panel B provides a detailed breakdown of specific digital competencies demanded within Clinical Laboratory Technologists and Technicians roles. Genetics, Computer Science, and Data Analysis are among the most prominent digital skill demands. Genetics skills, making up 18.7% of the skill mentions in 2022-23, are essential for conducting genetic tests and research. Technologists with expertise in digital competencies from genetics can use genetic engineering technologies for gene editing and sequencing, which are crucial for advanced diagnostic and therapeutic research.

Computer Science skills, making up 8.6%, are vital for developing algorithms, managing and maintaining systems. Laboratory technologists with strong computer science backgrounds can design and implement robust data management systems by providing comprehensive data management solutions.

Data Analysis skills, accounting for 7.6% of the digital skill mentions, are critical for interpreting large volumes of laboratory data. Effective data analysis enables technologists to derive meaningful insights from their data, supporting evidence-based conclusions and enhancing the validity of their research findings. Advanced data analysis techniques, such as those implemented in SAS (Statistical Analysis System) and SPSS (Statistical Package for the Social Sciences), are increasingly important in laboratory settings for identifying trends and making informed decisions.

Figure A B.2 Panel C highlights the specific AI competencies sought within Clinical Laboratory Technologists and Technicians roles. Visual Image Recognition dominates the AI skill demands, accounting for 27.6% of the total AI skill mentions in 2022-23. Visual image recognition technologies, like those used in digital pathology, can analyse medical images to detect anomalies, providing valuable support to laboratory technologists in diagnosing and treating diseases. These tools leverage deep learning algorithms to interpret complex medical images with high accuracy, aiding in faster and more accurate diagnoses.

Machine Learning skills are also significant, making up 20.8% of the AI skill mentions. These techniques, have the capability to analyse extensive datasets and uncover patterns that might be challenging to discern through manual analysis. In clinical laboratories, these algorithms can be employed to forecast patient outcomes, streamline testing procedures, and tailor patient care according to specific individual data.

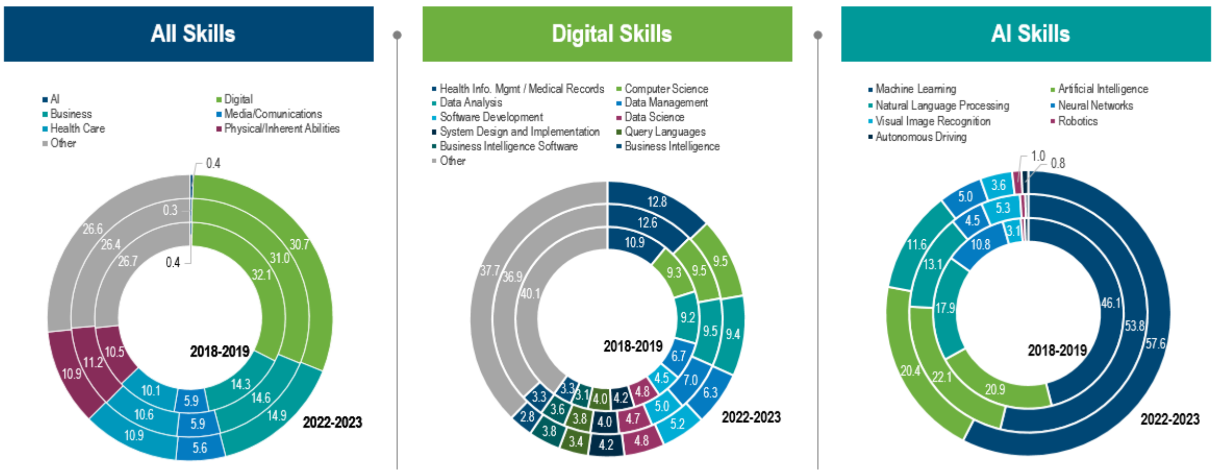
Artificial Intelligence skills represent 20.2% of the AI skill mentions, reflecting the broader adoption of AI technologies to automate complex tasks and enhance data interpretation. AI-driven tools can analyse lab test results to detect patterns and provide insights that enhance the accuracy of laboratory diagnostics.

Finally, to a lesser extent (10.4% of the AI skill mentions), Natural Language Processing (NLP) skills are also in demand, mostly to analyse textual data. NLP methods, like those utilised in the Natural Language Toolkit (NLTK) for Python, are useful at extracting crucial information from medical records, scholarly articles, and patient feedback. This allows laboratory technologists to integrate various data sources into their analyses. This ability is especially valuable for conducting systematic reviews and meta-analyses, where there is a need to process and analyse substantial amounts of text.

United States: Health IT professionals

The analysis of skill demands within Health IT Professionals roles in the United States reveals a clear trend towards increasing integration of digital and AI competencies.

Figure A B.3. Health IT professionals: A characterisation of the skill demand in the United States



Source: OECD based on Lightcast data.

Figure A B.3 Panel A presents the share of various skill types out of the total skill mentions for Health IT Professionals in the United States. Digital skills are the most prominent, making up 30.7% of the total skill mentions in 2022-23. This emphasises the critical role of technological competencies in health IT roles. The demand for digital skills indicates the necessity for health IT professionals to manage complex data systems, utilise advanced software tools, and incorporate technology into health operations. For example, digital tools for electronic health records (EHRs) are essential for managing patient data efficiently, enhancing the accuracy of data collection, and improving overall health delivery.

Business skills demands are also mentioned significantly, reaching 14.9% of the total skill mentions for the occupations in 2022-23 as effective business skills facilitate the planning, execution, and monitoring of IT projects, leading to successful outcomes.

Results in Figure A B.3 Panel B provide a detailed breakdown of specific digital competencies demanded within Health IT Professionals roles. Health Information Management and Medical Records lead the digital skill demands, accounting for 12.8% of the mentions in 2022-23. Skills in managing health information systems are crucial for maintaining patient records, ensuring data accuracy, and facilitating secure information exchange. Tools like Cerner and Epic Systems are widely used for these purposes, highlighting the importance of these competencies.

Computer Science skills play an important role in developing algorithms, managing and maintaining systems. Health IT professionals with strong computer science backgrounds can design and implement robust data management systems that support complex health activities. For instance, SQL and NoSQL databases are fundamental in managing health data effectively.

In addition, Data Analysis skills, accounting for 9.4% of the digital skill mentions, are critical for interpreting large volumes of health data. Effective data analysis enables health IT professionals to derive meaningful insights, supporting evidence-based decision-making and enhancing the validity of health data. Advanced data analysis techniques, such as those implemented in Python and R, are increasingly important in health for identifying trends and making informed decisions.

Figure A B.3 Panel C highlights the specific AI competencies sought within Health IT Professionals roles. Machine Learning is the most prominent AI skill, accounting for 57.6% of the AI skill mentions in 2022-23. Artificial Intelligence skills represent 20.4% of the AI skill mentions, reflecting the broader adoption of AI technologies to automate complex tasks and enhance data interpretation. AI-driven tools can analyse medical images to detect anomalies, providing valuable support to health IT professionals in diagnosing and treating diseases.

Notes

[1] In the Lightcast Skills Taxonomy, the Business category includes a range of skills essential for various business functions and operations, covering subcategories in a varied range of specialities, such as human resources, project management and business management.

[2] https://deepmind.google/discover/blog/codoc-developing-reliable-ai-tools-for-health/

Annex C. Methodology for estimating O*NET task-level potential automatability scores

The methodology for estimating the potential automatability of health occupations using large language models (LLMs), leverages the U.S. O*NET occupational structure, which provides detailed descriptions of tasks across various health occupations.

The U.S. ONET occupation structure for health occupations encompasses more than 1 600 core tasks across 97 health occupations, categorised under Health Practitioners and Technical Occupations (group 29) and Health Support Occupations (group 31). On average, each occupation includes 16 core tasks, each accompanied by expert-generated statements that describe the task comprehensively. For example, tasks for "Dentists, General" (ONET-SOC Code 29-1021.00) include specific activities such as "Remove diseased tissue, using surgical instruments", "Apply fluoride or sealants to teeth" and "Administer anaesthetics to limit the amount of pain experienced by patients during procedures."

For assessing the potential automatability of these tasks, the study employs the OpenAI's GPT-4 Turbo – the newest model available at that moment – to generate task-level potential automatability scores. This approach builds on the similar methodologies developed by Eloundou et al. (2023[15]), Eisfeldt et al. (2023[16]), and ILO – Research Department (2023[17]). Two automating technologies are considered in this study: Generative AI (GenAI) and Advanced Robots (AR).

The process to assess the likelihood for automatability of each task involves using sequential API calls to the GPT-4 model, each call tasked with evaluating the potential for a given task to be automated by either GenAI or AR. For each task, the model receives a detailed description of the task and is asked to provide an automation score ranging from 0 to 1. Table A C.1 contains the prompts used.

Table A C.1. Prompts used for generating task-level potential automatability scores

Role in GPT	Generative AI	Advanced Robots
System	You are a skills and AI expert. The user will provide you with a table of occupations and associated tasks, as well as specific instructions. Follow these instructions closely. Consider that Generative AI (Gen AI) is a type of AI that can create new data based on patterns it learns from existing data.	You are a skills and AI expert. The user will provide you with a table of occupations and associated tasks, as well as specific instructions. Follow these instructions closely. Consider that Advanced Robots are automated machines capable of performing tasks autonomously or semi-autonomously.
User	Evaluate and score the potential for automating each task in the corresponding occupation using current Generative AI technology. Scores should range from 0 (Gen AI cannot perform the task due to lack of necessary skills) to 1 (Gen AI can perform the task as effectively as a human worker). Provide your answer in the following JSON format: {"sc_genai": [scores], "rs_genai": [explanation for scores (60-90 tokens)]}. [list of occupation-task pairs]	Evaluate and score the potential for automating each task in the corresponding occupation using current Advanced Robots (AR) technology. Scores should range from 0 (AR cannot perform the task due to lack of necessary physical capabilities) to 1 (AR can physically perform the task as effectively as a human worker). Provide your answer in the following JSON format: {"sc_robot": [scores], "rs_robot": [explanation for scores (60-90 tokens)]}. [list of occupation-task pairs]

Note: Thew role "System" provides GPT with a general context of the task, while the role "User" contains the inquiry the model will answer.
Source: Authors' elaboration.

To ensure robustness of the results, this process is repeated three times for each task, and the final score used in the following analyses corresponds to the average of the three rounds. This iterative approach helps mitigate any variability in the model's responses and provides a more reliable estimate of the task's potential for automation. The scores generated by the GPT-4 model offer valuable insights into which tasks within health occupations are most susceptible to automation.

Estimating an occupation-level potential automatability score

Once scores are estimated, they are grouped by detailed occupation using a weighted average. The weights correspond to the task importance score provided by O*NET. This rating indicates the degree of importance of a particular descriptor (task) to the occupation. The possible ratings range from "Not Important" (1) to "Extremely Important" (5). This approach allows the analysis to capture the significance of each task within an occupation, providing a more nuanced understanding of potential automatability.

The methodology follows the approach developed by the ILO Research Department (2023[17]), offering a view on how susceptible each occupation is to automation by Generative AI (GenAI) or Advanced Robots (AR). In particular, the weighted average automatability score (μ) reflects the mean potential automatability of tasks within an occupation. The weighted standard deviation (γ) measures, instead, the dispersion of automatability scores across different tasks within the same occupation. Table A C.2 shows the results obtained for the 97 health occupations, it also includes the inferred shares of physical/manual and cognitive tasks used to create the overall automatability score.

Table A C.2. Occupation-level scores obtained from GPT-4

O*NET Code	Occupation	N. tasks	Avg. GenAI	SD GenAI	Avg. AR	SD AR	Physical (%)	Cognitive (%)
29-1011.00	Chiropractors	11	0.20	0.15	0.04	0.07	0.18	0.82
29-1021.00	Dentists, General	20	0.13	0.12	0.25	0.24	0.35	0.65
29-1022.00	Oral and Maxillofacial Surgeons	11	0.06	0.04	0.19	0.25	0.55	0.45
29-1023.00	Orthodontists	11	0.14	0.05	0.06	0.07	0.00	1.00
29-1024.00	Prosthodontists	11	0.19	0.13	0.32	0.22	0.36	0.64
29-1031.00	Dietitians and Nutritionists	13	0.55	0.17	0.06	0.06	0.00	1.00
29-1041.00	Optometrists	10	0.26	0.17	0.10	0.14	0.10	0.90
29-1051.00	Pharmacists	14	0.54	0.14	0.22	0.20	0.00	1.00
29-1071.00	Physician Assistants	12	0.32	0.18	0.15	0.22	0.17	0.83
29-1071.01	Anaesthesiologist Assistants	5	0.18	0.09	0.53	0.38	0.20	0.80
29-1081.00	Podiatrists	10	0.14	0.17	0.17	0.22	0.30	0.70
29-1122.00	Occupational Therapists	16	0.38	0.15	0.16	0.19	0.06	0.94
29-1122.01	Low Vision Therapists…	19	0.33	0.15	0.10	0.14	0.05	0.95
29-1123.00	Physical Therapists	23	0.25	0.16	0.20	0.20	0.13	0.87
29-1124.00	Radiation Therapists	19	0.37	0.19	0.47	0.31	0.16	0.84
29-1125.00	Recreational Therapists	11	0.28	0.10	0.10	0.13	0.00	1.00
29-1126.00	Respiratory Therapists	20	0.29	0.20	0.28	0.25	0.25	0.75
29-1127.00	Speech-Language Pathologists	17	0.48	0.15	0.05	0.07	0.00	1.00
29-1128.00	Exercise Physiologists	25	0.43	0.20	0.26	0.27	0.12	0.88
29-1129.01	Art Therapists	22	0.36	0.15	0.04	0.05	0.00	1.00
29-1129.02	Music Therapists	30	0.37	0.17	0.06	0.11	0.03	0.97
29-1141.00	Registered Nurses	15	0.40	0.20	0.27	0.21	0.13	0.87
29-1141.01	Acute Care Nurses	22	0.32	0.18	0.19	0.25	0.14	0.86
29-1141.02	Advanced Practice Psychiatric Nurses	20	0.28	0.14	0.04	0.10	0.00	1.00
29-1141.03	Critical Care Nurses	29	0.30	0.18	0.26	0.28	0.17	0.83
29-1141.04	Clinical Nurse Specialists	30	0.40	0.17	0.05	0.06	0.00	1.00

O*NET Code	Occupation	N. tasks	Avg. GenAI	SD GenAI	Avg. AR	SD AR	Physical (%)	Cognitive (%)
29-1151.00	Nurse Anaesthetists	24	0.15	0.09	0.26	0.25	0.25	0.75
29-1161.00	Nurse Midwives	20	0.25	0.16	0.15	0.23	0.10	0.90
29-1171.00	Nurse Practitioners	27	0.36	0.19	0.09	0.13	0.04	0.96
29-1181.00	Audiologists	22	0.40	0.19	0.15	0.19	0.05	0.95
29-1211.00	Anaesthesiologists	16	0.21	0.20	0.11	0.17	0.19	0.81
29-1213.00	Dermatologists	16	0.20	0.17	0.16	0.22	0.06	0.94
29-1215.00	Family Medicine Physicians	11	0.34	0.21	0.03	0.04	0.00	1.00
29-1216.00	General Internal Medicine Physicians	16	0.27	0.17	0.07	0.11	0.06	0.94
29-1217.00	Neurologists	22	0.29	0.16	0.07	0.14	0.00	1.00
29-1218.00	Obstetricians and Gynecologists	14	0.22	0.19	0.05	0.08	0.07	0.93
29-1221.00	Pediatricians, General	13	0.26	0.15	0.04	0.04	0.00	1.00
29-1222.00	Physicians, Pathologists	14	0.46	0.21	0.10	0.16	0.00	1.00
29-1223.00	Psychiatrists	11	0.32	0.16	0.01	0.02	0.00	1.00
29-1224.00	Radiologists	15	0.43	0.23	0.18	0.22	0.00	1.00
29-1229.01	Allergists and Immunologists	14	0.34	0.21	0.05	0.10	0.00	1.00
29-1229.02	Hospitalists	14	0.33	0.18	0.06	0.09	0.00	1.00
29-1229.03	Urologists	14	0.24	0.20	0.21	0.27	0.21	0.79
29-1229.04	Physical Medicine and Rehabilitation Physicians	15	0.24	0.14	0.09	0.11	0.00	1.00
29-1229.05	Preventive Medicine Physicians	15	0.45	0.18	0.04	0.04	0.00	1.00
29-1229.06	Sports Medicine Physicians	26	0.33	0.20	0.11	0.15	0.04	0.96
29-1241.00	Ophthalmologists, Except Pediatric	16	0.20	0.17	0.10	0.12	0.13	0.88
29-1291.00	Acupuncturists	18	0.23	0.18	0.17	0.20	0.28	0.72
29-1292.00	Dental Hygienists	14	0.28	0.18	0.39	0.29	0.57	0.43
29-1299.01	Naturopathic Physicians	19	0.23	0.14	0.07	0.10	0.16	0.84
29-1299.02	Orthoptists	16	0.24	0.12	0.10	0.18	0.00	1.00
29-2011.00	Medical and Clinical Laboratory Technologists	12	0.62	0.11	0.48	0.23	0.08	0.92
29-2011.01	Cytogenetic Technologists	28	0.52	0.19	0.43	0.29	0.14	0.86
29-2011.02	Cytotechnologists	12	0.43	0.25	0.47	0.27	0.25	0.75
29-2012.00	Medical and Clinical Laboratory Technicians	6	0.61	0.23	0.63	0.23	0.17	0.83
29-2031.00	Cardiovascular Technologists and Technicians	10	0.49	0.19	0.47	0.32	0.30	0.70
29-2032.00	Diagnostic Medical Sonographers	18	0.36	0.20	0.37	0.25	0.22	0.78
29-2033.00	Nuclear Medicine Technologists	14	0.49	0.21	0.49	0.22	0.07	0.93
29-2034.00	Radiologic Technologists and Technicians	27	0.43	0.22	0.55	0.21	0.22	0.78
29-2035.00	Magnetic Resonance Imaging Technologists	21	0.35	0.20	0.48	0.24	0.24	0.76
29-2051.00	Dietetic Technicians	10	0.55	0.14	0.18	0.19	0.00	1.00
29-2052.00	Pharmacy Technicians	13	0.59	0.26	0.69	0.15	0.31	0.69
29-2053.00	Psychiatric Technicians	12	0.28	0.17	0.24	0.28	0.33	0.67
29-2055.00	Surgical Technologists	14	0.26	0.12	0.69	0.10	0.50	0.50
29-2057.00	Ophthalmic Medical Technicians	18	0.35	0.18	0.62	0.19	0.33	0.67
29-2061.00	Licensed Practical and Licensed Vocational Nurses	15	0.28	0.14	0.46	0.22	0.47	0.53
29-2081.00	Opticians, Dispensing	21	0.39	0.19	0.45	0.24	0.24	0.76
29-2091.00	Orthotists and Prosthetists	14	0.34	0.19	0.36	0.24	0.14	0.86
29-2092.00	Hearing Aid Specialists	9	0.44	0.16	0.39	0.22	0.11	0.89
29-2099.01	Neurodiagnostic Technologists	16	0.31	0.20	0.38	0.29	0.25	0.75
29-2099.05	Ophthalmic Medical Technologists	29	0.33	0.18	0.51	0.29	0.14	0.86
29-2099.08	Patient Representatives	8	0.54	0.15	0.05	0.06	0.00	1.00

O*NET Code	Occupation	N. tasks	Avg. GenAI	SD GenAI	Avg. AR	SD AR	Physical (%)	Cognitive (%)
29-9091.00	Athletic Trainers	20	0.29	0.19	0.23	0.24	0.40	0.60
29-9092.00	Genetic Counselors	19	0.48	0.18	0.02	0.04	0.00	1.00
29-9093.00	Surgical Assistants	23	0.19	0.15	0.55	0.24	0.65	0.35
29-9099.01	Midwives	34	0.24	0.18	0.14	0.19	0.18	0.82
31-1121.00	Home Health Aides	11	0.19	0.19	0.41	0.27	0.73	0.27
31-1122.00	Personal Care Aides	8	0.21	0.14	0.24	0.20	0.50	0.50
31-1131.00	Nursing Assistants	26	0.19	0.14	0.57	0.24	0.62	0.38
31-1132.00	Orderlies	8	0.19	0.15	0.77	0.11	1.00	0.00
31-1133.00	Psychiatric Aides	15	0.23	0.18	0.36	0.27	0.53	0.47
31-2011.00	Occupational Therapy Assistants	21	0.34	0.15	0.24	0.22	0.14	0.86
31-2012.00	Occupational Therapy Aides	12	0.36	0.17	0.50	0.21	0.42	0.58
31-2021.00	Physical Therapist Assistants	18	0.33	0.22	0.49	0.28	0.61	0.39
31-2022.00	Physical Therapist Aides	13	0.31	0.25	0.59	0.27	0.69	0.31
31-9011.00	Massage Therapists	13	0.17	0.20	0.25	0.21	0.46	0.54
31-9091.00	Dental Assistants	14	0.37	0.20	0.58	0.23	0.43	0.57
31-9092.00	Medical Assistants	19	0.48	0.23	0.59	0.22	0.47	0.53
31-9093.00	Medical Equipment Preparers	11	0.58	0.12	0.78	0.15	0.27	0.73
31-9094.00	Medical Transcriptionists	13	0.81	0.08	0.35	0.31	0.00	1.00
31-9095.00	Pharmacy Aides	8	0.46	0.27	0.57	0.30	0.50	0.50
31-9097.00	Phlebotomists	17	0.26	0.19	0.56	0.24	0.53	0.47
31-9099.01	Speech-Language Pathology Assistants	8	0.46	0.19	0.27	0.21	0.00	1.00
31-9099.02	Endoscopy Technicians	12	0.34	0.18	0.55	0.28	0.50	0.50

Source: Authors' calculations based on sequential calls to GPT4 model through the OpenAI API and O*NET data.