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Artificial Intelligence for Public Use

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Abstract

This paper investigates the economic and societal impacts of Artificial Intelligence (AI) in the public sector, focusing on its potential to enhance productivity and mitigate labour shortages. Employing detailed administrative data and novel occupational exposure measures, we simulate future scenarios over a 20-year horizon, using Sweden as an illustrative case. Our findings indicate that advances in AI development and uptake could significantly alleviate projected labour shortages and enhance productivity. However, outcomes vary substantially across sectors and organisational types, driven by differing workforce compositions. Complementing the economic analysis, we identify key challenges that hinder AI's effective deployment, including technical limitations, organisational barriers, regulatory ambiguity, and ethical risks such as algorithmic bias and lack of transparency. Drawing from an interdisciplinary conceptual framework, we argue that AI's integration in the public sector must address these socio-technical and institutional factors comprehensively. To unlock AI's full potential, substantial investments in technological infrastructure, human capital development, regulatory clarity, and robust governance mechanisms are essential. Our study thus contributes both novel economic evidence and an integrated societal perspective, informing strategies for sustainable and equitable public-sector digitalisation.

Keywords: Artificial intelligence; Implementation of technology; Productivity; Labour demand

JEL Codes: E24, J23, J24, N34, O33.

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1. Introduction

The public sector in developed countries increasingly faces the challenge of reconciling an increase in demand for its services with decreases in revenues and labour supply, partly due to an ageing population (Crowe *et al*, 2022, Dougherty *et al*, 2022, Causa *et al*, 2025). The public sector is crucial for social welfare and constitutes a substantial part of the economies, providing critical welfare services, such as judiciary, defence, educational and healthcare services. On average, the sector amounts to almost half of GDP and a fifth of total employment across OECD countries (OECD, 2023, Lupi *et al.*, 2024). However, it is troubled by challenges, such as, population ageing, climate change and geopolitical tensions, which are associated with an increase in demand for health and defence services, strains on public finances, and labour shortages. Without structural reforms that, for example increase efficiency in the public sector, it will be difficult to sustain citizens' expectations of welfare services, both for financial and labour supply reasons.[1]

To address current and future challenges of the public sector, several actors are setting their hope to Artificial Intelligence (AI) (EU, 2024, Draghi, 2024, Starmer, 2025, Sweden, 2023). The expectations are that AI can be used to improve services, reduce administration, and boost productivity in the public sector. In the last 10-15 years, there has been tremendous progress in AI technologies, recently attracting the attention of the public with the introduction of generative AI chatbots, such as Claude and ChatGPT. Many scholars view these technologies as so-called general purpose technologies, which are associated with increased productivity and economic growth (Bresnahan and Trajtenberg, 1995, Goldfarb *et al.*, 2023, Bresnahan, 2024, Eloundou *et al.*, 2024). Others point out issues with AI, particularly in the public sector, such as, a lack of explainability, hallucinations, bias, and issues of accountability, as well as identified risks with AI (Lidskog, 2020, White and Lidskog, 2021, Farrell *et al.*, 2023, Selander *et al.*, 2023, Mitchell, 2024, Slattery *et al.*, 2024).

[1] The public sector is already struggling to attract and keep workers with the necessary competence, and this is expected to worsen in the next decades (Causa *et al*, 2025).

In this paper, we investigate whether these expectations and worries are warranted or not. We start by introducing a simple conceptual framework that bridges economics with insights from other disciplines. We then carry out detailed scenario analyses of the economic potential for using AI in the public sector to raise productivity and reduce the risk for labour shortages, over the next 20 years. Having simulated the economic outcomes, we analyse broader societal challenges related to putting AI for public use, connecting these challenges to the conceptual framework.

To rigorously perform the scenario analyses, we employ a novel set of measures of the occupational exposure to AI technologies and apply it to universal and individual-level administrative data for Sweden. Sweden is advantageous as a case study because of its detailed and comprehensive administrative data. In addition, the results can illustrate the potential for other countries. If Sweden, which already has an already efficient public sector and relatively digitalised economy, can grow productivity and reduce labour shortages using AI, other countries could possibly reap even larger gains.[2] Our scenarios incorporate detailed labour demand forecasts and feature different trajectories in the development as well as use of different AI technologies in the public sector.

We make two contributions to the literature. First, we provide novel evidence on the economic impact of AI by investigating the public sector. Despite of the challenges to the public sector and interest in using AI to enhance its efficiency, there are, to the best of our knowledge, few, if any, studies on the efficiency potential of AI in the public sector. There is a nascent and growing empirical literature on the economic impacts of AI.[3] However, data scarcity is an issue, which is why studies often have been carried out at the aggregate level or for small samples of firms, while another set of studies focus on the potential to automate work in specific occupations, employing so-called AI occupational exposure measures (e.g.,

[2] In Sweden, the public sector is only slightly larger than average in the OECD in terms of the expenditure share of GDP, while it is the second largest in terms of share of total employment, consistent with an already relatively efficient sector.

[3] Lane and Saint-Martin (2021) and OECD (2023) provide an overview.

Georgieff and Hyee, 2022, Fossen and Sorgner, 2022, Felten *et al.*, 2019). Recently other types of studies, e.g., performing experiments, or using job vacancy data, have emerged, indicating the productivity-enhancing effect of generative AI in specific tasks and the association between AI-hiring and firm growth as well as firm structural transformation (Brynjolfsson *et al*, 2023, Dell'Acqua, 2024, Acemoglu *et al.*, 2022, Babina *et al*, 2024).

Second, we contribute to the literature on societal digital transformation by analysing both opportunities and challenges with public AI use from an interdisciplinary framework that integrates insights from economics, governance, ethics and socio-technical systems. This ensures a more holistic view of AI in the process of digitalisation in society than is common in the literature.

In the scenario-analyses, we find that without further use of AI in the public sector, which is our baseline scenario, labour demand will increase by 15 percent in 20 years, and average productivity growth will be a mere 0.2 percent per year. In contrast, in our main scenario, AI advances and uptake will result in a 11 percentage point decrease in labour demand, while the annual average productivity growth will more than tripple to 0.7 percent. However, the outcomes differ substantially across and within sub-sectors of the public sector. For example, some municipalities experience substantially higher productivity growth than other municipalities, driven by differences in occupational workforce composition.

In our review of hinders and risks in the public sector, we find that public organisations face multiple challenges associated with AI use. These include, e.g., skills shortages, complex or unclear rules and regulation, data- and algorithm-related issues and limitations, costs, insufficient leadership, and an absence of strategies for AI adoption.

To conclude, our study indicates that efficiency can be substantially improved and labour shortages mitigated using AI. However, to realise this, while considering the particularities of the public sector, would likely require substantial investments and careful attention to known risks, known unknown risk, and implications, e.g., for unequal access to welfare services.

The rest of the paper is organised as follows. In Section 2., we introduce our conceptual framework. In Section 3., we present our empirical approach for the scenario analyses, including data. In Section 4., we display and discuss our results from the simulations. In Section 5., we review evidence on the main challenges with using AI in the public sector. In Section 6., we make concluding remarks. (Additional results and technical details are provided in the Online Appendix.)

2. Conceptual Framework

AI is a socio-technical system–with expectations but also presence in existing infrastructure–whose future uptake and impact in the public sector depends on the economic and sociopolitical factors, as well as tacit and codified rules. To frame our analysis, we therefore draw on insights from several fields, including economics and sociology.

The *economic perspective* builds on the task-based model of labour markets, where technological change reallocates tasks between workers and technology (Acemoglu and Restrepo, 2019). AI-driven automation can displace labour by assuming routine tasks previously performed by workers, thus potentially reducing overall labour demand even as productivity rises—the displacement effect. Conversely, technological progress may also introduce new tasks requiring human skills, generating new employment opportunities—the reinstatement effect, although this effect may occur later in time than the displacement effect. In addition, AI may augment workers in the remaining tasks, raising productivity and increasing labour demand (Bessen *et al*, 2022). The net impact of AI on employment and productivity, therefore, emerges from these competing forces and their timing.

However, the public sector also operates within strict *ethical and legal frameworks* that shape the application of AI as well as its consequences. Moreover, the broader sociopolitical context, with its power structures, goals, and expectations, also strongly influences which

AI is developed and in which areas it is deemed central. Importantly, as risk research has pointed out, is that the narrative surrounding a new technology (perceived risks and benefits) strongly influences society's investment in and implementation of it. Social science research highlight the seemingly paradoxical danger of underestimating or overestimating the capacity of AI (current and future) (Collins, 2018, Lobo and Del Ser, 2024). Underestimating its capacity will lead to a loss of control, overestimating it – attributing more intelligence to it than it actually possesses - will lead to poor decision-making. And both cases will lead to unintended consequences and a suboptimal adaptation of society to AI (not having a realistic expectations). This is emphasized in the Bletchley Declaration (2023), signed by 28 countries from all continents, including Brazil, China, the European Union, India, and the United States, which states that AI presents enormous global opportunities but also significant risks, and therefore requires international regulation. Creating and disseminating *knowledge about AI* among users is therefore necessary but not sufficient for appropriately assessing and deploying AI in the public sector.

Governance is key for AI to beneficially used, especially in the public sector (Acemoglu, 2021, Acemoglu and Johnson, 2023). Since data is often biased and algorithms may cause harm, such limits of AI-technology can maintain and reinforce stereotypes and make decisions that lead to increased inequality. This, in turn, can create a loss of democratic legitimacy and public distrust in authorities and institutions (Beckman *et al*, 2024, Obermeyer *et al.*, 2019). In response to these threats, the importance of transparency, accountability, and, ultimately, public trust has been emphasized (Busuioc, 2021, Ross, 2024). These values are important but not without challenges. AI is not only opaque to its users (and even more so to its non-users), but also professionals involved in its development have incomplete knowledge beforehand of how an AI-based system will work in practice. There is a risk that deploying systems, trained on certain situations in more varied environments, can result in "long tail" events and cascade failures. It is therefore important to create insight into the limits of current knowledge ("known unknowns") as well as preparedness for things can happened that was impossible to know beforehand ("unknown unknowns") (White and Lidskog, 2021). Such insights, and more generally societal impacts as well as tradeoffs, need to be reflected upon by AI-professionals in the development, deployment and assessment of AI in the public sector, again raising the need for competence development.

AI has the potential to create innovation and increase productivity in the public sector. Therefore, it is both critical that the risks identified above are prevented or appropriately managed, and that regulatory ambiguity is avoided, which otherwise can impede beneficial implementation of AI in the public sector. This can be achieved through an effective governance framework for AI that includes strategic leadership, adaptive oversight, scenario planning, inclusive stakeholder dialogues, and mechanisms to address the inherent uncertainties of AI systems (White and Lidskog, 2021, Korinek, 2023). Thus, successful AI implementation requires consideration of technological capabilities, necessary infrastructure, appropriate and consistent regulation, institutional readiness, and societal values.

In summary, AI-driven digitalisation in the public sector is important, but depends on several factors, of which technical aspects being just one of them. To enable and effectively design AI investments in the public sector, it is essential to have knowledge regarding AI, as well as economic dynamics, institutional conditions and the special characteristics of the public sector, including its core values.

3. Scenario Analysis Approach

To investigate the potential economic impact of public AI use, anchored in the conceptual framework, we employ scenario analysis. Our focus on productivity and labour demand.[4] This allows us to consider how different assumptions on AI advances and implementation in the public sector would affect outcomes. The results are indications of impacts, not forecasts, since everything else is unchanged. Thus, the results under different scenarios are useful for

[4]The approach draws on Baily *et al.* (2023) and has similarities with Acemoglu (2024), while being substantially different, e.g., in specifically analysing the public sector and in the detailed input and output, using universal administrative data and a novel AI exposure measure.

comparing alternative futures, all else being equal.[5]

The scenario analysis presumes that AI technologies that are available will be used and thereby affect how public administration is carried out, and this transformation results in impacts on labour productivity. We interpret such impacts as the result of the displacement and the complementation effects of the conceptual framework. Improvements in labour productivity will reduce labour demand at current levels of output in the public sector. The AI-induced transformation necessitates complementary investments, e.g., in competence development and technical infrastructure to improve the efficiency of the public sector.

We carry out this analysis in several steps.[6] First, we combine administrative data on individuals in Sweden with a measure of their exposure to AI advances, based on their detailed occupation. Here we only keep individuals employed in the public sector. The administrative data include information on the occupation and employer organisation all individuals ($\geq$ 15 years), and is from the so-called Longitudinal Integrated Database for Health Insurance and Labour Market Studies (LISA) (Ludvigsson *et al.*, 2019).[7] The AI measure is the Dynamic AI Occupational Exposure index (DAIOE) of Engberg *et al* (2024), which is available both for AI overall and for different subdomains of AI, as well as for generative AI (genAI), with the genAI measure building on the language modelling and image generation subdomains. The DAIOE index matches advances in AI technologies with granular data on skill requirements in detailed occupations from the U.S. sponsored O*NET occupational database.

Second, our first (baseline) scenario is constructed. We update our database of public sector employees according to forecasts of SCB (2023a) regarding future labour demand in different

[5]Other limitations are that the simulations do not consider: potential indirect impacts from connections to other parts of the economy; potential minimum human labour occupational requirements in occupations; quality improvements from AI and related impacts; and other factors, e.g., geopolitical or migration developments. More generally, national accounts imperfectly measure digital services contribution to welfare (Brynjolfsson *et al*, 2025).

[6]For an overview of the steps, see Figure B1 in the Online Appendix.

[7]LISA data is for year 2020, which are then updated, see next paragraph. Reassuringly, using data for 2020 rather than a more recent year hardly affects the occupational composition, see Figures D1-D5 in the Online Appendix.

occupations and an assumed annual productivity growth of 0.2 percent.[8] Thus, in our baseline, we take a 20 year perspective, meaning that our baseline is the public workforce composition in 2044, taking "normal" productivity growth into account, without any further implementation of AI, compared to today.

Third, for our other scenarios, we simulate the productivity and labour demand year-by-year based on the AI exposure of the public workforce and assumptions about both further advances and increased public uptake of AI technologies. The productivity impacts of AI are fully implemented in the most exposed occupations, and in other occupations according to their level of exposure. The impacts on the whole or parts of public sector are proportional to the shares of employees with a certain exposure level (Hulten, 1978). The resulting productivity and labour demand changes over the 20 year period is then compared with those in the baseline, capturing the potential for progress and uptake of AI to make the public sector more efficient and more able to mitigate labour shortages. These differences are presented for: the 20 most common occupations in the public sector; sub-sectors of the public sector, based on ownership (state, region, and municipality); and sub-sectors according to the OECD Classification of the Functions of Government (COFOG).

Next, we turn to the details of our scenarios $2-4$–the ones with further AI uptake and progress.[9] Our second scenario is a conservative one. We assume that the recent advances of AI research up to 2023, the most recent year of our DAIOE measure, gradually are implemented in the public sector according to its detailed occupational exposure. However, we assume no further AI research progress. In this scenario, productivity increases with 10 percent in the most exposed occupation, until year 2044. This is arguably a conservative level of productivity increase, considering both experimental and quasi-experimental studies on the impacts of generative AI (e.g., Brynjolfsson *et al*, 2023, Noy and Zhang, 2023).

In scenario three, which is our main (and "moderate") scenario, we assume higher increases

[8]Measuring productivity growth in the public sector is challenging, easily underestimating actual growth. We take this number from an estimation in the UK, based on an improved approach (ONS, 2023).

[9]For an overview of the scenarios, see Figure B26 in the Online Appendix.

in productivity levels than in scenario two, with a particularly high impact for occupations in accordance with their exposure to generative AI. For genAI, we assume a 10 percent higher productivity in 10 years time, for the most exposed occupation, while other AI applications lead to a 5 percent higher productivity in their most exposed occupations. This means that occupations that would be the most exposed both to generative and other types of AI would see a 15 percent increase in productivity by 2034. In addition to these short-run impacts, we assume a more general advance and uptake of AI over the total 20 year period. The third scenario also features enhanced productivity growth. AI often is considered a general purpose technology, and as such it can be expected to increase productivity growth, especially as it has the potential to increase efficiency in research and development, spurring technological and scientific progress. We let general annual productivity growth increase to 0.25 percent, while adding maximum 0.10 percentage units in accordance with AI exposure.

Our final scenario (number four) is mostly similar to scenario three but features higher increases in both productivity levels and growth–this is our "optimistic" scenario. The genAI impacts until 2034 are here 15 percent and 10 percent for other AI, while 30 percent for AI overall over the whole 20 year period, that is, till 2044. Here general annual productivity growth increases to 0.30 percent, while adding maximum 0.15 percentage units in accordance with AI exposure. A new feature in this scenario is that we pay attention to the potential of joint advances in AI and robot technologies. While there has been expectations that by now this would, e.g., have resulted in an increasing share of cars being fully self-driving, the obstacles have to date been insurmountable but in specific environments or cities (Suchan *et al.*, 2021). However, intense research efforts and signs of progress would seem to suggest that AI-infused robots would in the next few decades be able to assist or automate work that is also requiring psychomotor and physical abilities. We therefore assume that this results in maximum 25 percent increase in productivity in occupations in relation to their exposure to robotics, using a novel robot exposure index.[10]

[10]The measure (DAIOE ROE) is constructed from a survey in 2024 among engineering university students

4. Economic Results

Employing our empirical approach, we present the main results from our scenario analysis, with additional ones being available in the Online Appendix.

In the baseline scenario, we assume no further public AI uptake and advances in AI technologies. This means that productivity and labour demand will be determined by existing low levels of productivity growth and forecasted changes in occupational labour demand. The productivity results are presented in Figure 1, and the labour demand ones in Figure 2. We find that public productivity will have increased by 4 percent by 2044, while labour demand will have increased by 16 percent. Labour demand increases are the highest in social protection and health, with, e.g., the demand for auxiliary nurses having increased by 20 percent (Online Appendix Tables C1-C3.)

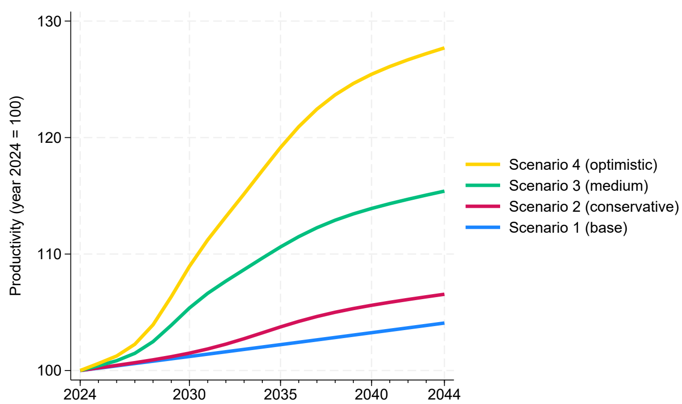

Figure 1: Simulated productivity trends for the public sector

Note: The figure shows how productivity is predicted to evolve for the public sector as a whole, for the simulated scenarios, until the year 2044.

Moving on to scenario two, as AI gradually is adopted and slightly raises productivity, labour demand diminishes somewhat compared to in the baseline, particularly in central government. The labour demand increase is higher in some occupations that are more AI

on the abilities of robotics in 19 psychomotor and physical abilities of the U.S. government sponsored O*NET database. Comfortingly, robustness analysis shows that the DAIOE ROE is strongly positively correlated with the robot exposure index of (Webb, 2020), see Figure C16 in the Online Appendix.

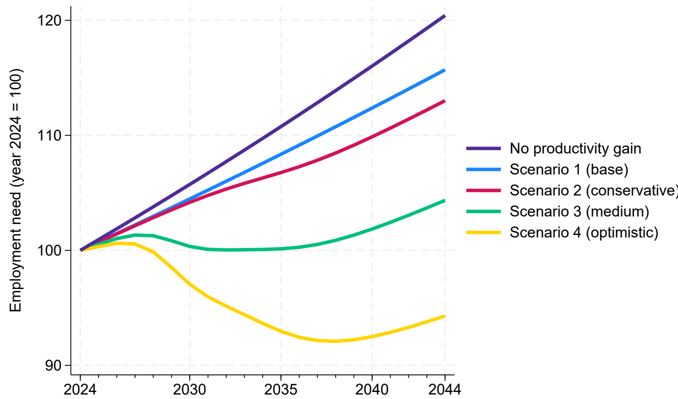

Figure 2: Simulated labour demand for the public sector

Note: The figure shows how productivity is predicted to evolve for the public sector as a whole, for the simulated scenarios, until the year 2044. The productivity gains are here assumed to lead to equivalent labour savings. For example, if productivity doubles, then the demand for labour is halved.

exposed, such as, clerical occupations and civil engineers.

The third scenario is our main one. It features a second wave of technological progress in AI overall, and particularly in genAI, that results in higher productivity levels, and higher annual productivity growth. Compared to the baseline, productivity increases by 11 percentage units, leading to an annual growth of 0.7 percent, compared with 0.2 in the baseline–more than three times the baseline growth. The implication for labour demand is substantial. Instead of an increase in labour demand of 15 percent, we see a 4 percent increase. In some sectors, we even find a slight reduction labour demand, such as in central government. For occupations with high exposure to genAI and other AI, such as policy administration professionals, productivity will have increased with more than 25 percent, between 2024 and 2044 (see Figure B5 in the Online Appendix). Though this may seem high, we regard this as relatively modest, considering the rapid advances in technology in recent years, their potential for both automation and augmentation, and widespread absorption of the technology, e.g., in occupations such as software developers.[11] Nevertheless, a development as in scenario three would be most helpful in mitigating expected labour shortages in the public sector.

[11]The overall increase in productivity of 15 percent, instead of 4 percent in the baseline, is quite modest compared with the ones for the overall economy in some other recent studies for the USA (Baily *et al.*, 2023, **?**).

Finally, in the fourth scenario, AI advances and uptake in the public sector together with progress in robotics set the scene for a productivity increase of 24 percentage units beyond the baseline. As a result, labour demand in the public sector decreases by 6 percentage units, and by 12 percentage unites in central government. The only functional area where labour demand still increases, but only marginally, is social protection. Since technology now is applicable also in occupations that are intense in psychomotor and physical abilities, their productivity increases. For example, the common occupation of auxiliary nurse now experiences an 11 percent increase in productivity, instead of 4 percent in the baseline. Still, labour demand in that and many other common occupations will be relatively unchanged. This is, however, a significant change compared to the large increases in demand in the baseline scenario.

An advantage with our approach is that is allows us to study the impact across but also within sectors, using data at the organisational level, such as government agencies, and municipalities as well as their publicly owned enterprises. In Figure X, we display the results per scenario and sub-sector according to ownership. In all three scenarios with advances in AI and AI uptake, the productivity impacts are the largest at the state level, and smaller at the regional and municipality levels.

However, also within sectors and scenarios, there are relatively large heterogeneity in impacts. This suggests that AI advances benefit some organisations within a sector substantially more than others. In the simulations, this is driven by differences in the occupational workforce composition of organisations within a sector. For example, a higher share of employees in occupations that require a university degree means a higher exposure to the abilities of AI. Differences in occupational workforce composition could, e.g., stem from different missions, priorities, or labour supply. This is indicated by the average annual productivity growth in our main scenario being below 0.5 in the policy area of social protection and more than twice that rate in general public services (see Fig C17 in the Online Appendix).

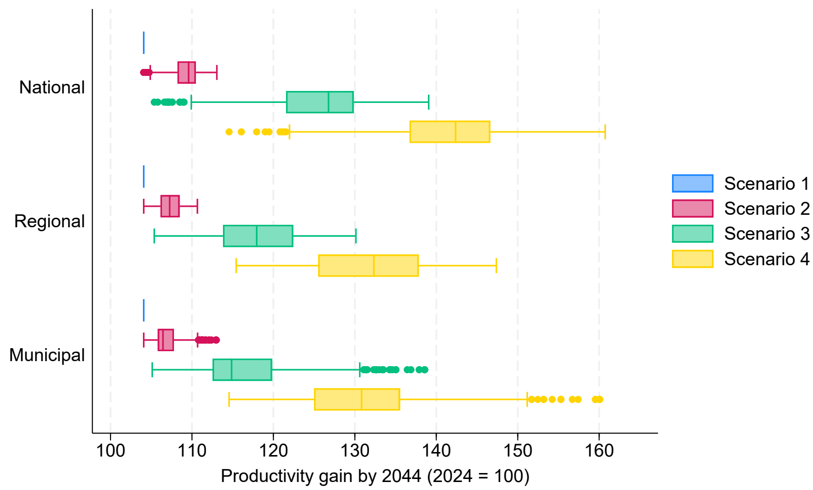

Figure 3: Distributions of organisations' productivity changes to 2044, by sub-sector

Note: The box plot shows how organisations' productivity gains to 2044 are distributed, by scenario and sub-sector. The five vertical lines in each box-and-whisker represent the following percentiles: 0, 25, 50 (median), 75, 100. Outliers are marked with points.

Heterogeneity in impacts from AI advances could exacerbate existing differences within a sector, for example, municipalities. Municipalities have vastly different abilities to cater for the needs of their citizens, let alone, invest in AI, while their services are largely stipulated by laws or regulations or may be expected by the citizens. In Sweden, over the last five decades, such differences have already increased.[12] This implies that with AI, organisations in the municipal sector with more resources may be able to use those resources more efficiently, facilitating welfare provision, while other organisations that already struggle may not be able to exploit AI, lagging even further behind.

5. Challenges with AI Use

The adoption of AI in the public sector faces several interconnected challenges that limit its effective integration and use. Although AI offers potential productivity gains, as discussed in the conceptual framework and indicated in the simulations, these outcomes are not guar-

[12]Between 1973 and 2023, the mean population size of a municipality increased by almost a third, the smallest municipality had lost about a third of its population, and the largest one had almost doubled. In 2023, a quarter of municipalities have less than $10,000$ inhabitants.

anteed due to significant institutional barriers (Wirtz *et al.*, 2019). Sweden serves as an illustrative example, reflecting broader international experiences.

In Sweden, approximately 25 percent of central government authorities and an equal share of municipalities report using AI, while more than 60 percent of regions use AI (SCB, 2023b). Other surveys in Sweden indicate an increased use, in particular, in the form of pilot projects, for example, in municipalities. Among central government authorities, the pattern would seem to suggest that AI is primarily used in administrative support services rather than in core welfare services to citizens. Using job postings by public organisations in the largest online job postings site in Sweden, which is run by the Public Employment Agency, we find a surge in the postings of jobs that require AI competencies, particularly in central government authorities (see Figures B14-B15 in the Online Appendix.)

Noting the increased but still limited and mostly experimental use of AI in the public sector, we turn to evidence on barriers to further AI adoption. These surveys provide a consistent picture (e.g., SCB, 2023b, Akavia, 2024). In Figure 4 we display responses from professionals in the public sector on why their organisations do not use AI more. As in other surveys, two areas stand out. First, lack of knowledge and competence is a major hinder. It is not only about employees themselves, but also about lack of managerial AI competence. Second, issues regarding legality and security for using AI and data for AI use are important barriers. A third area is related to the lack of AI solutions - thus, related to technical limitations with AI that is available. Notably, these major obstacles are relatively similar across levels of government (central government, regions, and municipalities).

In light of our conceptual framework, and these evidence, we would like to highlight four key challenges that need to be addressed for the successful and effective use of AI in the public sector: challenges related to technical limitations; accountability, ethical and legal risks; organisational barriers in the form of limited financial capacities, competence, and lack of strategic leadership; and regulatory ambiguities. The fourth challenge is also related

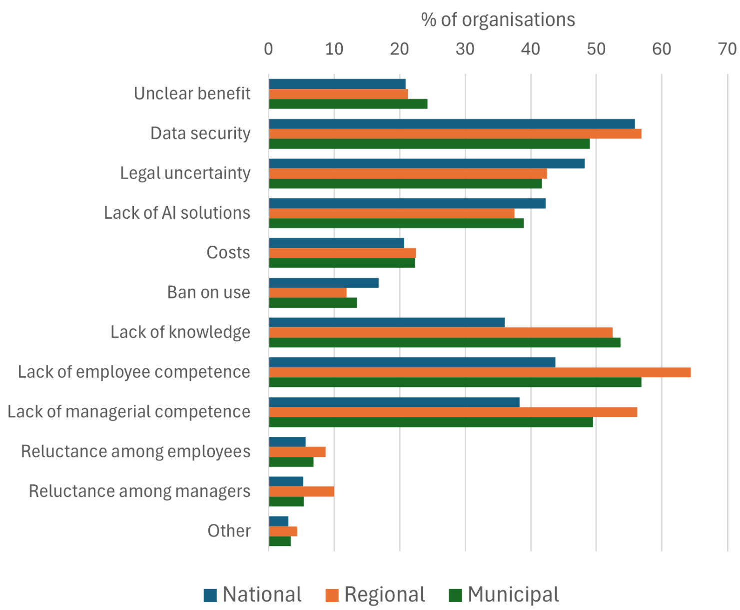

Figure 4: Reasons why organisations in the public sector are not using AI, 2024

Notes: Results from a member web panel carried out by Akavia, the union for white collar professionals, in May 2024. Percentage of respondents who answered affirmatively to the following question: "In your opinion, is one or more of the following factors an obstacle for increased use of AI in the organisation where you work? (Multiple options are possible)." Data for the figure is based on responses from professionals in the public sector who answered all questions (N = 1,729). Own processing of Akavia (2024).

to the perceived issues surrounding legality and data security.

A fundamental issue relates to the inherent technical constraints of current AI systems. AI excels primarily at tasks with well-defined, repetitive patterns (shallow machine learning) but struggles in contexts that requires complex judgment, adaptive reasoning, and nuanced decision-making—characteristics, which characterises much of public administration. Even if AI, through deep machine learning, develops to achiev an intelligence different from one solely based on computational power, there is a risk that overestimating its current capacity will result in a backlash in form of decisions that may be rational from a rule-based perspective, but unacceptable for people, who include more contextual factors in their deliberations (Sejnowski, 2018). AI systems may also be derailed by details in the data, which may result in erroneous and even fatal conclusions.[13] To this can be added the tendency for generative AI systems to confabulate, with potentially serious consequences, for example, if used by medical doctors in clinical summary notes (Goodman *et al.*, 2024).

Moreover, many AI systems lack transparency, complicating the accountability of automated decision-making processes. AI professionals may also refrain from accepting full accountability, as noted by Orr and Davis (2020). The "black box" nature of algorithms makes it challenging for public authorities to justify or even understand AI-driven decisions, potentially undermining legal requirements for explainability, fairness, and a legal basis (Busuioc, 2021). Bias in AI systems further exacerbates ethical concerns, as unintentional discrimination arising from algorithmic decisions poses risks to equity and public trust (White and Lidskog, 2021). Human oversight could, in principle, mitigate algorithmic bias, but can be insufficient (Gaudeul *et al.*, 2025).[14]

These technical limitations intersect with significant legal and ethical risks, particularly concerning data privacy and protection. AI use and development frequently involves sensitive

[13]See case 2746 in OECD (2024), involving a fatal accident between an AI-assisted car and a pedestrian.

[14]See OECD (2024), May 5, 2020, involving an AI-fraud-detection system in the Netherlands being found to violate human rights and privacy. Meanwhile, humans also have biases and appropriately used, AI systems may assist in reducing them.

personal data, data that might be recovered from AI models. This creates tensions between exploiting data for AI services improvement and adhering to stringent data protection regulations such as GDPR (Veale *et al.*, 2018). Public sector organisations must balance the need for data-driven innovation against legal obligations and ethical considerations surrounding individual privacy, fairness, and transparency.[15] The regulatory landscape remains fragmented and uncertain. This contributes to hesitancy among public entities to adopt AI solutions that may expose them to compliance risks or public criticism, in absence of leaders who still provide the mandate to experiment with and implement AI (White and Lidskog, 2021, Statskontoret, 2024).[16] Therefore, the benefits of using AI may be foregone, for example, in administrative support services, where generative AI could be productively used on data that are neither sensitive, nor related to individuals.

Organisational barriers also substantially impede AI integration. Many public agencies, including their management, lack the necessary internal competencies, including foundational knowledge about AI and specialized technical expertise (Mergel *et al.*, 2019, Farrell *et al.*, 2023). A survey among professionals in 2024 suggested that lack of AI competence was both the main reason for not using AI among the professionals and for their organisations to not use AI more Akavia (2024).[17] The absence of appropriate skills leads to misaligned expectations, either through resistance or over-reliance on AI systems, resulting in suboptimal outcomes. Additionally, risk-averse cultures within public organisations, characterized by hierarchical structures and stringent accountability norms, typically inhibit experimentation and innovation. The rigidity of public administration processes, coupled with short-term budgeting practices and limited incentives for efficiency gains, further constrains the transformative potential of AI (Liebman and Mahoney, 2017, Mergel *et al.*, 2019, Busuioc, 2021).

[15] Complicating this is the focus of existing rules and regulations on privacy and data protection, institutions which were enacted when data was not by far as important for innovation in the public sector as today.

[16] Survey evidence point to legal uncertainty and data protection as key reasons for organisations not using AI more, see Figure 4 here and Figure B27 in the Online Appendix.

[17] See Figure 4 here and Figure B28 in the Online Appendix.

Institutional and structural challenges compound these issues. Public-sector entities operate under strict legal, administrative, and procedural frameworks, often not suited for rapid technological adoption (Mergel *et al.*, 2019). Procurement regulations, resource allocation models, and fragmented governance structures are examples of potential barriers for coordinated AI initiatives. Smaller or less-resourced municipalities and agencies often face heightened challenges due to limited financial capacities, creating disparities in AI adoption and exacerbating existing inequalities in public service provision (Wirtz *et al.*, 2019).

Moreover, the quality and accessibility of data—crucial for effective AI applications—often pose significant practical hurdles. Public datasets frequently remain siloed and poorly integrated, hindered by outdated IT infrastructures. Data-sharing practices are limited by stringent privacy regulations and traditional institutional secrecy, constraining the ability to leverage AI's full potential (Veale *et al.*, 2018). Efforts to enhance data interoperability and invest in modern IT infrastructure are essential prerequisites for successful AI deployment.

Addressing these multifaceted challenges requires recognizing AI as a socio-technical system, deeply embedded within organisational contexts and shaped by human, institutional, and ethical factors (Wirtz *et al.*, 2019). Achieving meaningful productivity improvements with AI involves substantial investments not only in technology itself and its infrastructure in terms of telecommunications, power, compute, algorithms and data. Investments are also needed in skills development at all levels, regulatory clarity, organisational reform, and robust governance frameworks (Busuioc, 2021). As in previous technological shifts, simply adopting the technology without making the necessary investments and transforming how things are done is not likely to future-proof the public sector (Wachter and Brynjolfsson, 2024, Brynjolfsson and Hitt, 2000). Thus, realising AI's potential in the public sector depends critically on aligning technological capabilities with institutional readiness and societal values. This requires strategic leadership for long-term engagement.

6. Concluding Remarks

The public sector faces substantial challenges that can limit its ability to provide the services that citizens expect. An ageing population and worsening skills shortages imply that fewer people will be expected to care for an increasing number of individuals, while expectations regarding both the quantity and quality of public services continue to rise. Additional challenges include persistently low public-sector productivity, geopolitical instability, climate change, and infrastructure in need of renewed investment.

While governments may consider AI deployment as a means to enhance efficiency and mitigate labour shortages, such deployment itself is associated with additional obstacles and risks.

In this paper, we use detailed administrative data and surveys to analyse the potential, barriers, and risks associated with AI for public use, employing Sweden as an illustrative case. We observe that AI is relatively frequently used, but largely in pilot projects rather than as fully integrated elements of public service administration and provision. We also simulate scenarios with varying levels of AI development and productivity impacts. These simulations indicate that without further AI development and deployment, labour demand in the public sector will increase substantially. However, even with moderate assumptions regarding AI development and adoption, annual productivity growth nearly triples and labour shortages are significantly alleviated.

Nevertheless, these outcomes are not guaranteed, primarily due to significant institutional barriers. We identify key challenges hindering AI's effective deployment, including organisational barriers such as insufficient strategic leadership and AI competence; regulatory ambiguity; and ethical risks, particularly algorithmic bias and lack of transparency.

We argue that the successful integration of AI in the public sector requires comprehensive attention to these socio-technical and institutional factors. Otherwise, AI might offer limited benefits in productivity improvements and labour shortage mitigation, while simultaneously introducing negative consequences associated with its use.

To realise AI's full potential, significant investments in technological infrastructure, human capital development, regulatory clarity, and robust governance mechanisms are essential. Our study thus provides novel economic evidence alongside an integrated societal perspective, informing strategies for sustainable and equitable public-sector digitalisation.

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