Technical appendix: Detailed approach

A.1 Task data

The task statements come from the O*NET database, release 27.2,[1] and cover around 19,000 tasks across 923 O*NET-SOC occupations (798 at the six-digit SOC level used in the analysis). We map the resulting occupation scores to Norwegian employment (see A.3). The Norwegian civilian public employment base for 2025 contains 266 four-digit STYRK-08 occupations with positive allocated employment. Of the assessed task statements, around 13,000 belong to SOC occupations linked to these. For each task the assessment uses the statement text, its source occupation and its task type. O*NET types every task as either Core, central to the occupation, or Supplemental, peripheral to it. Both types are retained.

A.2 Task-level assessment

As a conservative starting point, we consider only the set of tasks that Eloundou et al. classify as exposed to AI and treat the rest as non-automatable.[2] Anthropic's Claude Opus 5 then assesses each of the remaining tasks by applying explicit written rules rather than an open-ended prompt. LLM-based task classification is established practice in this literature. Each task receives two judgements that narrow the potential down further. The first places it on a six-level scale of how much of it current AI could perform at the required quality – none, little, some, half, most or all – with work shares of 0, 10, 25, 50, 75 and 95 per cent. The standard is feasibility, not technical capability alone: the work must be within what current AI can perform and be performed while meeting the requirements of good administrative practice, and automation that would degrade service quality, equal treatment or citizen access does not count. The second judgement assigns the automatable share to one of two categories: off-the-shelf AI assistants, where a trained employee could do the work with a compliant AI assistant on material available to them, and tailored AI systems, where the process places demands on consistency, traceability, data protection or integration with existing systems.

The rules exclude from automation any task whose action is physical, whose value lies in the human relationship itself, or which is an accountable act such as a decision, negotiation or enforcement. Only separable supporting work receives a share. Borderline cases are resolved conservatively, choosing the lower share and the tailored AI category.

The rules were developed and iteratively refined into a written assessment guide before the model was applied to the full task set, and the guide was calibrated through manual review of the classifications for the largest public-sector occupations and by checking the results at task and occupation level.

A.3 From tasks to Norwegian occupations and FTEs

Occupation shares

Because O*NET does not report task-time shares, we assume that an occupation's automatable-work share equals the weighted mean of its task shares, with twice the weight given to Core as to Supplemental tasks, following Eloundou et al. The task statements thus stand in for the composition of work.

Occupational mappings

O*NET codes its occupations in the US SOC system, while Norwegian employment is coded in STYRK-08. Two mappings connect them.

We map SOC occupations to ISCO-08 using the US Bureau of Labor Statistics' 2010 SOC-to-ISCO map-

ping and 2010-to-2018 SOC mapping, with a handful of manually adjusted links, such as removing specialist physicians from generalist doctors. Where several SOC occupations correspond to one ISCO occupation, US employment from the 2022 Occupational Employment and Wage Statistics (OEWS) provides the weights.

STYRK-08 is the Norwegian implementation of ISCO-08. We map it to ISCO-08 using the recoding rules in the ISSP 2016 Norway documentation.[3]

Employment base

Employment is measured in FTE. Four-digit STYRK-08 FTE by occupation and public subsector come from Statistics Norway's (SSB) table 11418 for November 2025. Central government includes public hospitals; local government includes municipalities and counties. Public enterprises are excluded. Annual subsector totals are the average of the four non-seasonally adjusted quarterly observations in SSB table 11655 for 2025.

We retain published four-digit employment figures from SSB table 11418 for 2025, with November as the reference month. These account for 96.2 per cent of the final civilian FTE total. Published three-digit totals allow us to allocate a further 2.2 per cent to suppressed cells within the corresponding occupation groups and subsectors, using available employment shares and documented judgement. The resulting occupational distribution is then scaled to annual subsector totals, adding the remaining 1.6 per cent.

Because the analysis covers civilian public employment, we also use annual averages from SSB table 11658 to estimate military employment, including conscripts not covered by the wage statistics. We exclude armed-forces occupations, ISCO major group 0, after scaling. The resulting civilian analytical base is around 293,000 FTE in central government and 494,000 in local government, or 787,000 FTE in total.

We multiply employment in each occupation by its automatable share of work to estimate the automation potential in FTEs.

Monetary results value these FTEs using occupation-by-subsector monthly earnings from table 11418 for 2025, multiplied by 12, with pension and other costs added using the 2025 subsector cost ratios published in NOU 2026: 5, appendix 6, table 6.5.[4]

Workforce groups

We assign each four-digit STYRK-08 occupation to one of sixteen occupational families and combine these into four reporting groups. The groups are mutually exclusive and together cover the civilian employment base. Three-digit minor groups are mostly whole, but not always: economists, psychologists and social workers share a minor group yet sit in Administration, Health & Social Care and Other respectively.

A.4 Projection to 2035

We project Norwegian public employment from the 2025 base to 2035 by estimating how demand for public services changes. For health and care occupations, we derive growth rates from SSB's projected demand in the reference scenario, table 6.1, using the corresponding education group or the closest available group where there is no direct match.[5] The same growth rate applies in central and local government. For all other occupations, we let employment follow demographic demand, holding service coverage, standards and productivity constant, so that staffing per user remains fixed. Childcare and education occupations follow the age groups they serve and the remaining occupations follow the total population, both from SSB's population projection.[6]

SSB's projection implies that demand grows by 28 per cent for health care workers, 21 per cent for nurses and 16 per cent for doctors from 2025 to 2035, compared with 5 per cent for the total population. Applying the growth rates to the 2025 employment base raises civilian general-government employment from about 787,000 to 861,000 FTEs, an overall increase of 9 per cent.

Because this growth is concentrated in care work with low automatable shares, automation potential grows more slowly than employment, from about 90,000 to 96,000 FTEs. The automatable-work rate falls slightly but still rounds to around 11 per cent.

To keep the NOK amounts comparable with today's, we value the 2035 figures at 2025 labour-cost levels.

Table A1: Occupational families in the four workforce groups

Administration	Health & Social Care	Education & Childcare	Other
General office clerks and caseworkers	Social and health care workers	Pedagogues, pedagogical assistants and childminders	Science and engineering professionals and technicians
Secretaries	Nurses and midwives	Primary and lower-secondary school teachers	Social workers
Academic and communication professionals	Medical doctors	Post-compulsory and other education teachers	Police and emergency services
Managers	Other health occupations		Other remaining occupations
Legal professionals and associates			
199,000 FTE, 69 codes	323,000 FTE, 29 codes	197,000 FTE, 14 codes	142,000 FTE, 154 codes

Note: Group FTE in 2035 as projected in A.4, rounded to the nearest thousand. Codes are four-digit STYRK-08 occupations with positive allocated public employment in 2025. Rounded group totals need not sum to the rounded overall total.
Source: Own grouping of SSB's STYRK-08 occupations. FTE from SSB tables 11418, 11655 and 11658 for 2025, projected to 2035 as described in A.4.

A.5 Comparison with other estimates

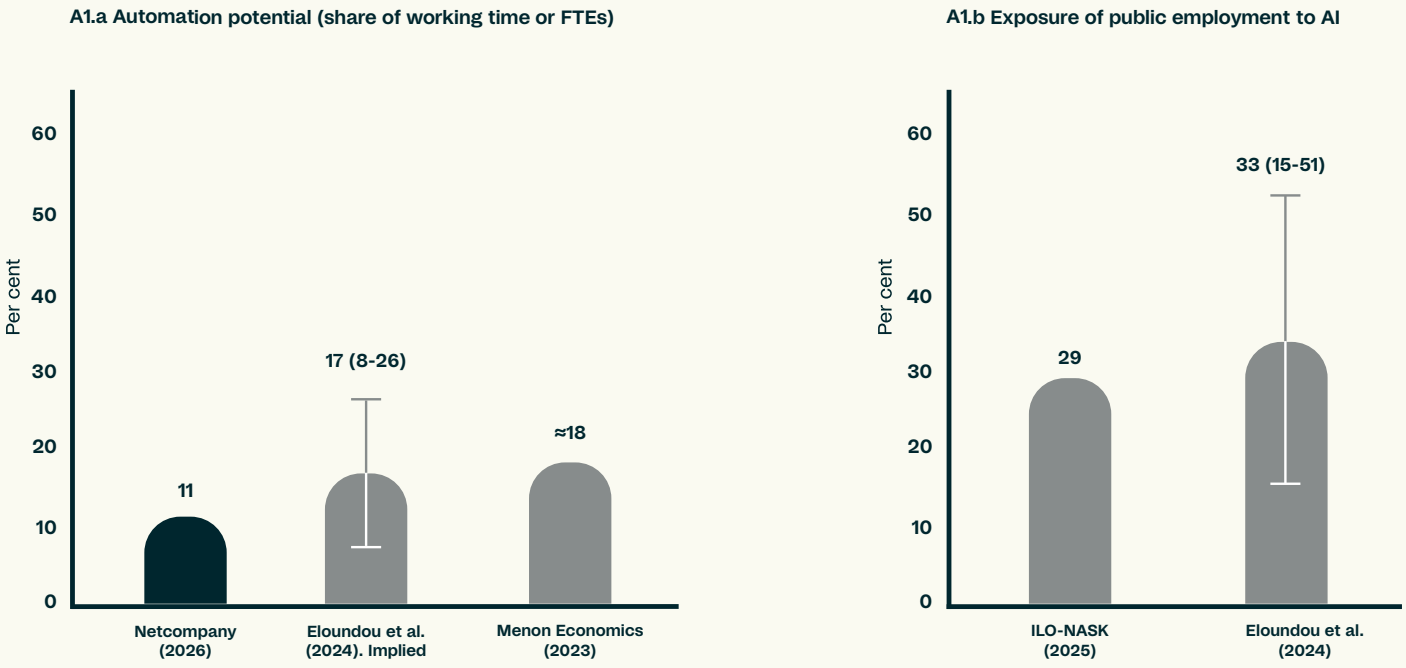
Figure A1 compares our results with previous estimates for Norwegian public services, with automation potential in panel a and exposure in panel b. The studies differ in sector coverage, assumptions and what they measure, so their estimates are not directly comparable.

Menon Economics estimates that full use of the language models assessed in 2023 could free the equivalent of 155,000 FTEs in public administration, education and health and social services, nearly 18 per cent of employment in those industries, private providers included.[7] The figure is a theoretical potential: GPT-4 classifies each O*NET task, and exposed tasks are assumed to take 60 per cent less time. The same study put the economy-wide potential at 17 per cent of working time, which the authors' later journal article lowered to 12 per cent.[8]

Implement Consulting Group (2025) estimates that widespread AI adoption could yield an annual productivity gain valued at NOK 26 billion in public administration, defence and social security, equivalent to 10 per cent of gross value added in these activities. This represents the potential to deliver more with the same resources. For non-market public services, gross value added is measured mainly by staff costs and depreciation.[9] Its broader 2024 study estimates an annual gain of around NOK 100 billion at widespread adoption across a larger group of service industries, including education, health and social services and private providers.[10]

For the economy as a whole, SSB finds that 16.8 per cent of working time could be automated with generative AI, assuming a 50 per cent time saving on exposed tasks.[11]

Figure A1: Our estimate is at the low end of Norwegian results for the public sector



Note: Panel a shows automation potential as a share of working time or FTEs; panel b shows employment-weighted occupational exposure scores. Netcompany: our preferred estimate for 2035. Menon: public administration, education and health and social services, including private providers. ILO–NASK and Eloundou: occupational scores applied by us to Norwegian public FTE in 2025. Eloundou bars show β and whiskers span α–ζ; the implied potential assumes a 50 per cent time saving on exposed tasks. Whiskers show alternative definitions, not confidence intervals.
Source: Own calculations, Menon Economics (2023), Gmyrek et al. (2025) and Eloundou et al. (2024).

The Tony Blair Institute's UK study is the closest in design, as it also divides the potential by the technology required. Regrouping its categories, free or low-cost tools account for about 55 per cent of its 20 per cent time saving and bespoke systems, sensory hardware and high-cost equipment for about 45 per cent, against almost three quarters requiring tailored AI systems in our estimate.[12]

We also apply two published occupational exposure indices to the 2025 public-employment base in A.3. The ILO–NASK (2025) index gives an employment-weighted mean of 29 per cent.[13] Eloundou et al. (2024) gives 33 per cent on their preferred measure, β, using the human ratings.[14] Both are means of occupational exposure scores, not estimates of time saved. Applying the 50 per cent task-time saving underlying Eloundou et al.'s definition implies a potential of 17 per cent, or 8 to 26 per cent using their narrower α and broader ζ measures.

Endnotes

[1] O*NET Resource Center, US Department of Labor, O*NET Database, release 27.2, 2023.

[2] Tyna Eloundou, Sam Manning, Pamela Mishkin and Daniel Rock, “GPTs are GPTs: Labor Market Impact Potential of LLMs”, Science 384, no. 6702 (2024): 1306–1308.

[3] ISSP 2016 Norway documentation, printed p. 22: STYRK-08 to ISCO-08 recoding rules.

[4] SSB, table 11418, November 2025 monthly earnings at full-time equivalents. Suppressed earnings use the occupation’s FTE-weighted mean across published government cells, then the subsector mean. Pension/other-cost ratios to wages are calculated from SSB’s preliminary national-accounts figures for 2025, published in NOU 2026: 5, Grunnlaget for inntektsoppgjørene 2026, Norwegian Ministry of Labour and Social Inclusion, appendix 6, table 6.5.

[5] SSB, Behov for og tilgang på arbeidskraft i offentlig helse og omsorg fremover, Reports 2026/18, table 6.1, demand in the reference alternative.

[6] SSB, tables 07459 (observed population) and 14740 (2026 population projection, main alternative MMM).

[7] Trygve Svalheim, John Oskar Skjeldrum, Sebastian Winther-Larsen, Kristoffer Midttømme and Jonas Erraia, KI: Betydning for arbeidsstyrken, Menon-publikasjon nr. 127/2023.

[8] Svalheim et al., “KI: betydningen for arbeidsstyrken”, Samfunnsøkonomen 6 (2024): 31–42.

[9] Implement Consulting Group, The AI opportunity for eGovernment, commissioned by Google, July 2025. See pp. 7 and 51 for the productivity estimate and method. For the national-accounts definition, see SSB, Concepts and definitions in national accounts, “Value added”.

[10] Implement Consulting Group, The economic opportunity of AI in Norway, commissioned by Google, May 2024, p. 16. The grouping covers NACE O–R and U, including arts, entertainment and recreation. The estimate is expressed at 2023 economic levels on an approximately ten-year adoption horizon.

[11] SSB, Potensielle effekter på sysselsetting av økt bruk av generativ kunstig intelligens, Notater 2025/15.

[12] Isabel Atkinson and James Browne, The Potential Impact of AI on the Public-Sector Workforce, Tony Blair Institute for Global Change, July 2024.

[13] Authors’ calculations using the published occupational scores from Paweł Gmyrek et al., Generative AI and Jobs: A Refined Global Index of Occupational Exposure, ILO Working Paper 140, ILO and NASK, May 2025.

[14] Authors’ calculations using the published human-rated occupational scores from Eloundou et al. (2024), mapped through SOC and ISCO to Norwegian public employment using the occupational mappings in A.3.