UNABRIDGED ENGLISH TRANSLATION — VERSION 2.2

AI's Impact on the Workforce – PHU01

An investigation into how agentic AI could affect the need for labour in Sweden through 2035

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PHU01, Per Högberg Investigation no. 01

Illustrated edition — version 2.2 (translation)

This is a complete, unabridged English translation of the Swedish-language report "AI:s påverkan på arbetskraften – PHU01", version 2.2 (UTGIVEN / published), 19 November 2026. All figures, tables and conclusions are translated as-is from the Swedish original; none have been recalculated. Figures reproduced as embedded images retain their original Swedish-language labels, since they are graphics rather than editable text; their captions below are translated and describe their content in full.

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Contents

- Summary
- 0. Preface, background and reading guide
- 1. Introduction (Per Högberg)
- 2. Labour volume and need 2025–2035
- 3. Concepts and evidence principles
- 4. What the empirical evidence shows
- 5. Method: how the scenarios are calculated
- 6. Results
- 7. Compensation and volume effects
- 8. Conditions and limiting factors
- 9. Value capture, financing and the tax base
- 10. Identified but unassessed problems
- 11. Courses of action
- 12. Monitoring and review
- 13. Concluding synthesis
- Appendix A. Type table and placement of occupational groups
- Appendix B. Results by occupational group (SSYK 2- and 3-digit)
- Appendix C. Rationale by impact type
- Appendix D. Source register
- Appendix E. Glossary
- Appendix F. “Visionen” – the author's conceptual background material (2025–2026)

Summary

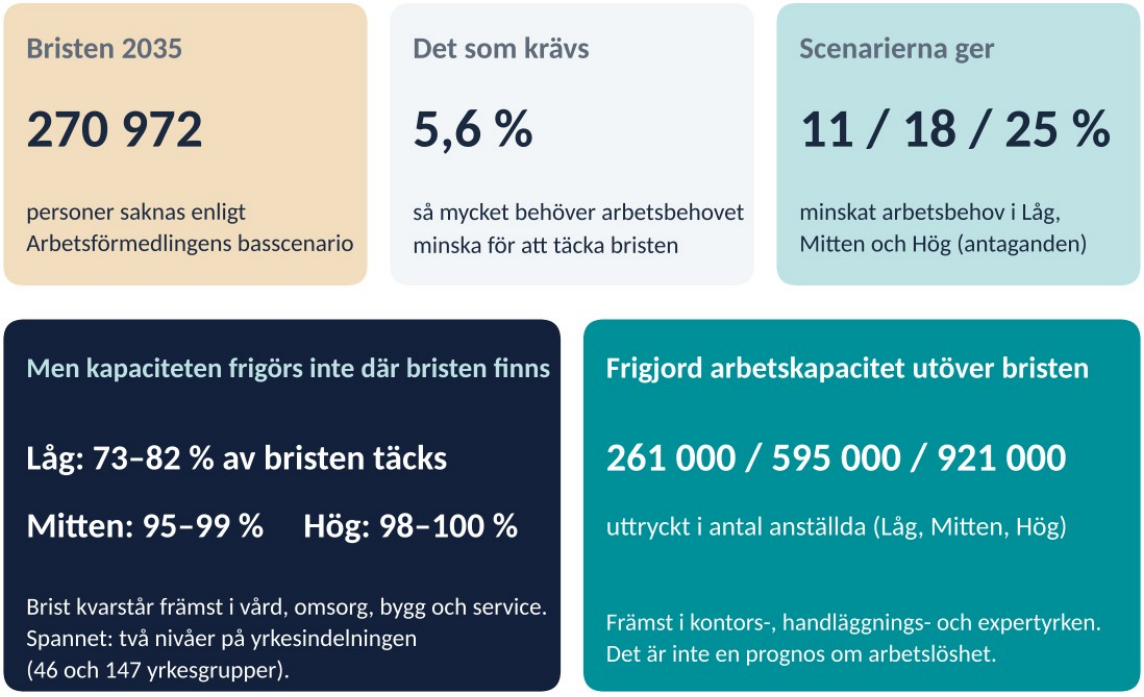


Figure 1. The investigation at a glance.

Source: Swedish Public Employment Service (AF) Analysis 2026:04 (K081, K082) and own calculation (sections 6.1, 6.2 and 6.5).

Sweden's Public Employment Service (Arbetsförmedlingen, AF) calculates that Sweden will have an additional labour shortfall of roughly 270,000 people by 2035 (270,972 in AF's own table appendix, base scenario). The shortfall is the difference between the labour demand AF projects to 2035 and the number of people who would be employed if nothing else changes. The investigation addresses how much of that shortfall agentic AI can help close, by letting the work be done by fewer people.

It cannot be answered with evidence. Agentic AI has only begun to see wider use during 2026. Essentially all measured effects, in Sweden and internationally, concern generative AI used in chat form only. They show no broad transformation of employment so far, but a weakened entry path into the labour market for young people in AI-exposed occupations. This is therefore a scenario investigation. The effect levels are the author's own assumptions, based on what is analysed in the report and reported and justified openly. The calculation should be updated as outcomes become measurable, at a recommended frequency of six months.

AI's greatest power is analysis, not administration. Agentic AI has most impact where large volumes of data can be gathered and analysed, so that patterns are discovered that people often do not see. This applies to casework and expert work alike, but also to areas such as care, where continuously collected data can give early signs of changes that need action. Documentation and administration is the part that is easiest to introduce first, but is assessed as not being the most important effect (section 3.2).

Headline results.

- To cover the entire labour shortfall, the need for labour would on average need to fall by 5.6% compared with today's number of employees, if the capacity freed up can be used in the occupations where the shortfall exists. That figure follows directly from AF's and Statistics Sweden's (SCB) statistics and does not depend on any assumption about AI.
- The three scenarios give a gross reduction in demand of **11.0%, 17.9% and 24.6%** (Low, Mid, High), corresponding to roughly 532,000, 866,000 and 1,192,000 people. All three are clearly above the 5.6% break-even.

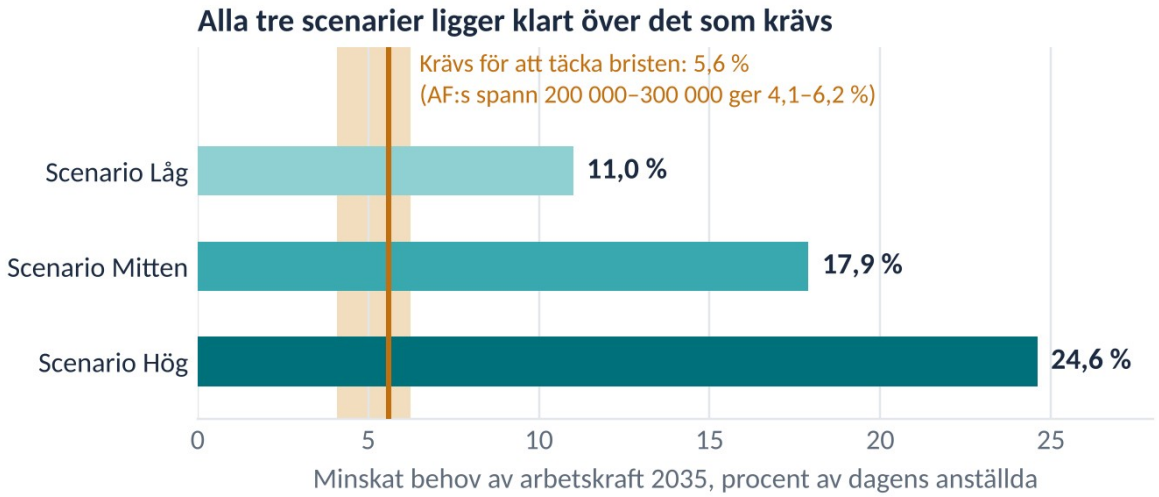


Figure 2. Reduced labour demand in 2035 under the three scenarios, compared with the reduction required to cover the shortfall.
Source: Own calculation (break-even per section 6.1, scenarios per table 6.2). Shortfall per AF Analysis 2026:04 (K081, K082).

- Without mobility between occupations, the shortfall is covered to 82% in Low and 99% in Mid when the calculation is made across 46 occupational groups. In Low, about 48,000 people of shortfall then remain, mainly in care, health care, construction and services. The same calculation at AF's own level of detail, 147 occupational groups, covers 73% in Low and 95% in Mid, leaving roughly 74,000 and 15,000 people of shortfall respectively (section 6.5). In care's largest shortfall occupations, 14–16% is required; the Low assumption (10%) is therefore not enough, while the Mid assumption (20%) is. The assumption for care is tested separately in section 6.6.
- Beyond the shortfall, labour capacity equivalent to roughly 261,000, 595,000 and 921,000 employees is freed up. The investigation calls this a surplus. In High this equals 19% of today's employees and 8.7% of the population. The surplus arises mainly in office, casework and expert occupations, where the shortfall is small. These figures are not a forecast of unemployment: how much of the capacity becomes fewer people employed depends on occupational mobility, new demand, new tasks and working hours (section 6.11).
- If lower prices lead to increased demand (volume compensation), the effect is reduced. The main calculation assumes no volume compensation and is therefore an upper bound. How large the compensation will be cannot be determined with today's evidence; with 50% compensation, 89% of the shortfall in Mid is still covered (sections 6.7 and 7).

Conclusion. The question is not whether AI can free up enough labour capacity in aggregate, but whether it is freed up where the shortfall exists. Sweden can have a labour shortage and a labour surplus at the same time.

The shortfall sits in care (37.5% of the entire shortfall); the freeing-up happens mainly in casework, offices and expert work. This makes occupational mobility, targeted AI use in care, and the question of how a surplus should be managed if it materialises (working hours, retirement age, financing and the tax base) the central political questions. These are addressed in chapters 9 and 11, and summarised in chapter 13.

0. Preface, background and reading guide

0.1 About the investigation

The investigation was produced by Per Högberg, chairman of the municipal executive board of Mullsjö Municipality, on his own initiative during the period June–November 2026. It has not been commissioned by any authority or organisation. The investigation was completed around the time the author visited Canada in late October 2026, to gain further international perspectives and input. Its purpose is to provide a basis for how workforce supply can be planned when labour is not sufficient, and what role AI can play.

0.2 How AI has been used in the work

The investigation was produced in collaboration with Claude models from Anthropic, primarily Claude Sonnet 5.5. Certain reviews and calculations, including the review and processing for this version, were done by Claude Opus 5.5, as well as Fable 5.2. ChatGPT has also been used at the review stage. The conclusions in the investigation are the author's, Per Högberg's, own, and were then processed and formulated primarily by Claude models.

Claude, an AI model from Anthropic, has searched for and compiled sources, built the calculation model according to the author's instructions, and drafted chapters. All assumptions in the model are the author's own. All source references can be traced to the source register (Appendix D).

Anthropic is itself a party to the development the investigation describes. The investigation uses no data from Anthropic as supporting evidence.

0.3 The author's background

Per Högberg has been chairman of the municipal executive board of Mullsjö Municipality during the period 2023–2026. Before that, Per worked in the IT sector 2007–2023, focused on business development within IT-supported operations in various parts of the world. Since 1998, Per has been engaged in work with the SAP business system, and since 2007 has taken part in the network he also led the founding of, SUGEN (SAP User Group Executive Network), an international gathering of independent associations for companies and organisations using the world's largest business system, SAP. Within SUGEN, several initiatives and ongoing responsibilities have focused on how business and process development can be supported through integrated systems where data can be analysed broadly for use in different ways.

Since 2007, Per's private company C-Business (Collaborative Business Sweden AB) has been a platform for carrying out initiatives such as this investigation. The company has not received funding for carrying out this investigation; funding has instead come from earlier income from other operations. Through his engagement as an industry researcher at Jönköping University, School of Engineering, since 2006, information modelling has been a main area of focus. When AI, and agentic AI in particular, emerged, the focus shifted to how it could be used to fundamentally change various functions in society, through integrated data sharing to optimise work processes.

Per sits on the Advisory Board of the School of Health and Welfare at Jönköping University (JU), where the focus today is on how research can help reduce the volume of care needed through improved public health. (Described in more detail in the forthcoming investigation PHU02 – The development of elderly care.)

During 2025 and early 2026, Per Högberg produced a series of vision documents, referred to here as “Visionen”, on how operations in the municipal sector can be developed with the support of agentic AI. The series comprises a shared base platform (“Basplattan”) and deep dives into administration and citizen contact, elderly care and schools (Appendix F). The work gave a concrete picture of what is technically possible in municipal operations and is part of the background to this investigation.

0.4 Interests and conflicts of interest

- Per Högberg was chairman of the municipal executive board in Mullsjö 2023–2026, a municipality with substantial need for fundamentally changed ways of working, through increased public health for all residents, to support and strengthen the economy in order to establish long-term sustainability of municipal services.
- Per Högberg is a member of the Swedish Association of Local Authorities and Regions' (SKR) standing committee on workforce supply (kompetensförsörjning). In the committee's work, the question of AI's impact on workforce supply has been discussed, and it has been established that there is a lack of investigations and calculations of it. This is one of the origins of this investigation (chapter 1). The committee has produced the action plan “Kraftsamling för välfärdens kompetensförsörjning” (2024, K160), which the investigation refers to in chapters 1 and 11.2. The investigation has not been commissioned by SKR and does not express SKR's or the committee's position.
- Per is a board member of SAPSA (the Swedish SAP User Association) and represents SAPSA in SUGEN (SAP User Group Executive Network), where companies' strategic use of agentic AI around the world is a focus area.
- Per's private company C-Business has financed the work on the investigation.
- The vision documents in Appendix F are the author's own. They are presented to show where the picture of what is technically possible comes from. They are not evidence of effects and are not a source for any value in the calculation.
- The investigation was produced with Claude models from Anthropic (see section 0.2). Anthropic is a party to the development the investigation describes.

0.5 How to read this investigation

- The investigation is a **scenario investigation**, not a forecast. The figures show what follows if the assumptions hold.

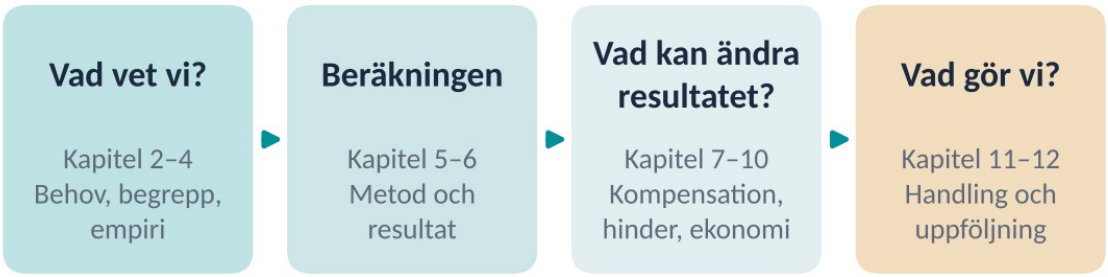


Figure 3. How the parts of the investigation fit together.

- Every figure describing something that has already happened is classified: **level 1** supply/capacity (someone offers something), **level 2** adoption (something is used), **level 3** outcome (measurable effect). A vendor's or company's statement about its own product or operations is always level 1.
- Every value in the calculation is marked by origin: **[Source]** value taken directly from a source, **[Reference]** an empirical value that does not concern AI and is only used in sensitivity analysis, **[Assumption]** the author's judgement with justification (section 3.4).
- The calculation rests on a simplification regarding the public sector: activities with a large public share, for example defence and parts of IT and expert services, are assumed in most respects to follow the same efficiency pattern as the private sector, possibly with some lag. This assumption is tested in section 6.7 and is not separately verified.
- Chapters 2–4 describe what is known. Chapters 5–6 are the calculation. Chapters 7–10 describe what could change the result. Chapters 11–12 are conclusions for action and follow-up. Chapter 13 gathers the investigation's conclusions on one page.
- The investigation is based on the material the investigation has reviewed up to November 2026. There may be studies and data that have not been found. The investigation should be updated on an ongoing basis, preferably every six months (chapter 12).

1. Introduction

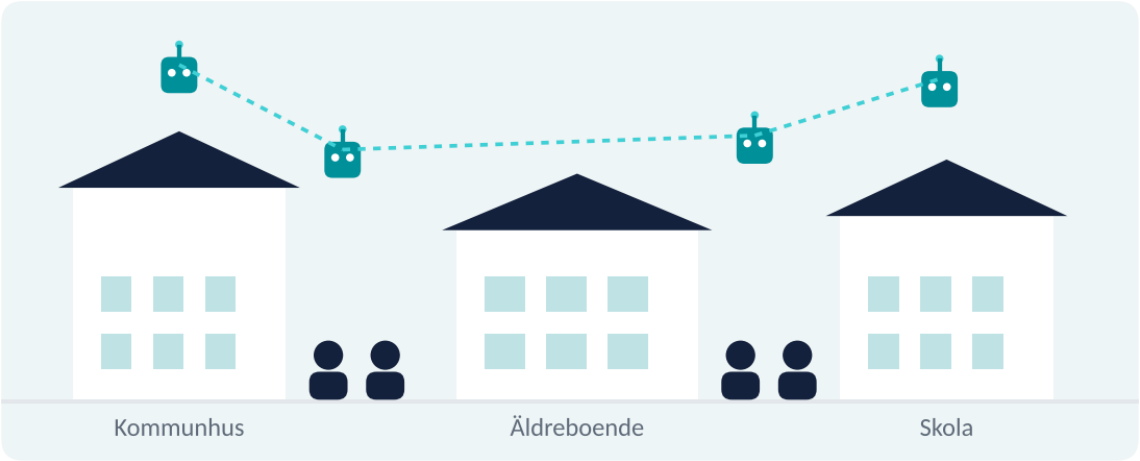


Figure 4. Agentic AI in municipal daily life: agents working across operations, with people at the centre (illustration).

The idea for this investigation grew during 2025–2026, when there appeared to be no answer to the question of AI's impact on the labour market, nor any published forecasts or scenarios. This is because it is a genuine challenge to build scenarios for business and process development that is not yet established in reality.

The background is the “Visionen” series described in section 0.3. That work showed what is technically possible, but not how large the effect would be on the need for labour. That question is the starting point for this investigation.

The investigation is also an initiative to contribute to the answer to the difficult question that, among others, the Swedish Association of Local Authorities and Regions' (SKR) standing committee on workforce supply, of which Per Högberg is a member, is working on: how is tomorrow's workforce supply to be solved? In its action plan “Kraftsamling för välfärdens kompetensförsörjning” (2024), the committee identified health-promoting factors, full-time work and a longer working life, and early transition, as the areas with the greatest effect (K160). At the committee's retreat in spring 2026, the impact of AI on workforce supply was discussed. The conclusion was that there is a lack of investigations and calculations of this, and that it would be valuable if such an investigation existed, since it could show what awaits Sweden. This is one of the origins of this investigation.

There are no simple answers to tomorrow's workforce supply, since moving people between occupations does not fully resolve the shortfall visible today. The answer being sought is rather: “through changed working methods, fewer people are needed to do what needs to be done”.

Many believe that IT, and not least AI, ought to be able to solve this. To understand that, one must understand what IT has long since done in terms of rationalisation: changed ways of working where machines, in the form of computers and robots – or looms, if we go a little further back in time – carry out parts of our processes.

So what exactly can AI do, and what actually is AI?

AI, artificial intelligence, is systems that interpret what a person wants done and carry it out by combining the knowledge held in the system.

In recent years, services such as ChatGPT have become synonymous with AI. ChatGPT and similar services are built on large language models (LLMs). They have knowledge of language and can ingest reference material, for example a rulebook or a book of law, and answer questions about what it says using ordinary human-like reasoning.

Agentic AI uses a language model to act on what happens. Based on rules and descriptions of how work should be done, the agent can carry out an activity when something occurs. If, for example, a sensor value exceeds a threshold, the agent can retrieve further values, call in staff or other functions, and gather what is needed for a relevant action. The experience can then be used to improve rules, material and models, so that the system becomes better at interpreting events and triggering the right activities. A language model does not, however, learn from itself at each use; the improvement requires that the experience is fed back in.

This can concern simple events, such as a flood, or more complex situations, where a staffing schedule needs to change due to altered workload or sickness. An agent then contacts the people who need to change their working hours, receives the responses, and continues until staffing reaches the level the rules require. But this is also where the human comes in: judging what should happen when the rules cannot be met. Sometimes a person says “we'll probably manage anyway today” – something a computer has no feel for – but with human judgement fed back into the process, the system can get better even at such trade-offs.

Describing the possibilities of AI in a few lines is difficult, but this gives a greatly simplified picture of what has happened and what is to come.

Effects and conclusions

The natural question then becomes: what does this mean?

Three scenarios have been calculated per occupational group: Low, Mid and High.

The time horizon is set at 2035, but it is today impossible to fully calculate when a full effect occurs.

When the shortfall that the Swedish Public Employment Service calculates for 2035, around 270,000 people (AF Analysis 2026:04), has been covered, a surplus remains of around 261,000 people in Low, 595,000 in Mid and 921,000 in High. In Low, a shortfall of around 48,000 people simultaneously remains in care, construction and services, since those freed up are mainly found in other occupations (chapter 6).

Evidence

The effects of agentic AI over the coming ten years cannot be calculated from evidence. The author's assessment is that the breakthrough for agentic AI came during 2026, and it is now that the capabilities are being developed and tested.

The investigation builds, among other things, on what has been measured about the use of language models. How major consulting, technology and software companies view and plan for the development, and the

expectations embedded in the large investments in AI, have been included as perspective and as a driver in the High scenario, but not as evidence of effect (section 9.3).

How automation and robotisation have previously changed the labour market has also been included in the material. However, probably never before has such a far-reaching change begun to occur across all types of operations simultaneously. No operation is assessed as unaffected, but the difference between occupational groups is large.

But it is now that we need to understand what the future may look like. This investigation is built on scenarios, not on measured effect.

Anyone using the investigation for labour-market planning in Sweden should therefore help update the calculations on an ongoing basis, preferably every six months, based on the effects gradually becoming visible in the labour market as agentic AI begins to be used widely across occupations.

Conclusion

In the High scenario, the surplus corresponds to around 19% of today's employees and 8.7% of Sweden's population. How the result might transfer to other countries with a similar labour market has not been investigated.

An important conclusion is that mobility between occupations becomes even more important than today: labour is freed up mainly in office, casework and expert occupations, while the shortfall is in care.

If the Mid or High scenario materialises, it is reasonable to test a gradual introduction of shorter working hours in the parts of the labour market where the surplus arises, and not to raise the target retirement age at the pace now following from the rules (sections 11.3–11.4).

Mullsjö, November 2026

Per Högberg

2. Labour volume and need 2025–2035

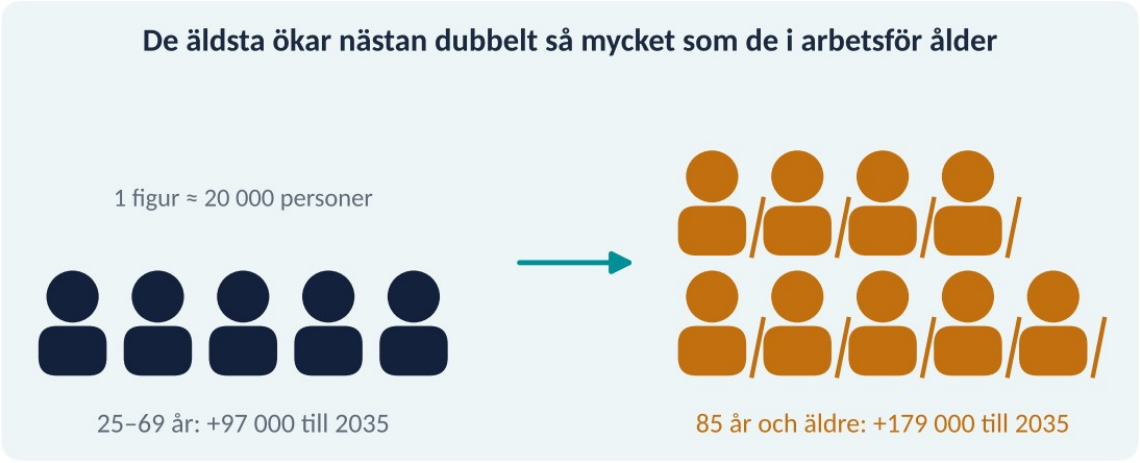


Figure 5. Population change 2025–2035: the group aged 85 and older grows more than the group aged 25–69 (illustration; one figure corresponds to roughly 20,000 people).

Source: Statistics Sweden (SCB), Sweden's future population 2026–2070 (K119).

2.1 Starting point: the Swedish Public Employment Service's calculation

The investigation's baseline for the shortfall is the Swedish Public Employment Service's (Arbetsförmedlingen, AF) analysis “Labour shortfall and labour from abroad” (AF Analysis 2026:04) with table appendix (K081, K082). In the base scenario, AF calculates an additional labour shortfall in 2035 of around 270,000 people; the table appendix sums to 270,972 across occupational groups. AF itself states a range of 200,000–300,000 depending on assumptions.

The baseline rests on normal economic growth, unchanged matching, full geographic mobility and no mobility between occupations. The shortfall is therefore not a measure of how many jobs stand vacant today, but of how much more labour demand is expected to grow than supply by 2035 if nothing else changes.

The investigation uses 270,972 as its calculation value, since it is the only figure available broken down by occupational group. The range 200,000–300,000 is reported as AF's own uncertainty interval. The break-even figure in chapter 6 (5.6%) becomes 4.1% at 200,000 and 6.2% at 300,000.

What the shortfall measures. AF projects labour demand to 2035 for 147 occupational groups (SSYK at 3-digit level) and each county, based on the National Institute of Economic Research's long-term scenario. Supply is the number employed in 2023 in each occupational group, projected forward with the population aged 20–64. The shortfall is the difference in the occupational groups where demand is greatest. It is counted in people, not full-time positions. It is an additional shortfall: it comes on top of shortfalls that already exist today and are partly handled through labour immigration, and AF assumes today's immigrated labour remains in place (K081, pp. 9–11 and appendix pp. 30–32).

AF's own caveats. AF states that the results are direct model outputs and should be read as indicators of direction and relative differences, not as forecasts. The model does not capture rapid technology shifts, and the baseline is therefore a picture without any AI effect. AF also notes that shortfalls in publicly funded occupations may be overestimated, since productivity there is assumed to grow slowly, and that the occupational groups are heterogeneous (K081, p. 11 and pp. 25–27).

The shortfall under other assumptions. Without mobility between counties, the shortfall becomes around 300,000 people (297,369 when the table appendix's county rows are summed). With full mobility between occupations as well, it becomes around 220,000. If, in addition, all registered jobseekers could be employed in the occupation they are seeking (perfect matching), it becomes 141,473 (K081, p. 27; K082). The difference between 270,972 and 141,473, around 129,500 people, shows how much those currently outside employment could contribute. This is a separate route to workforce supply alongside AI and is addressed in section 11.2.

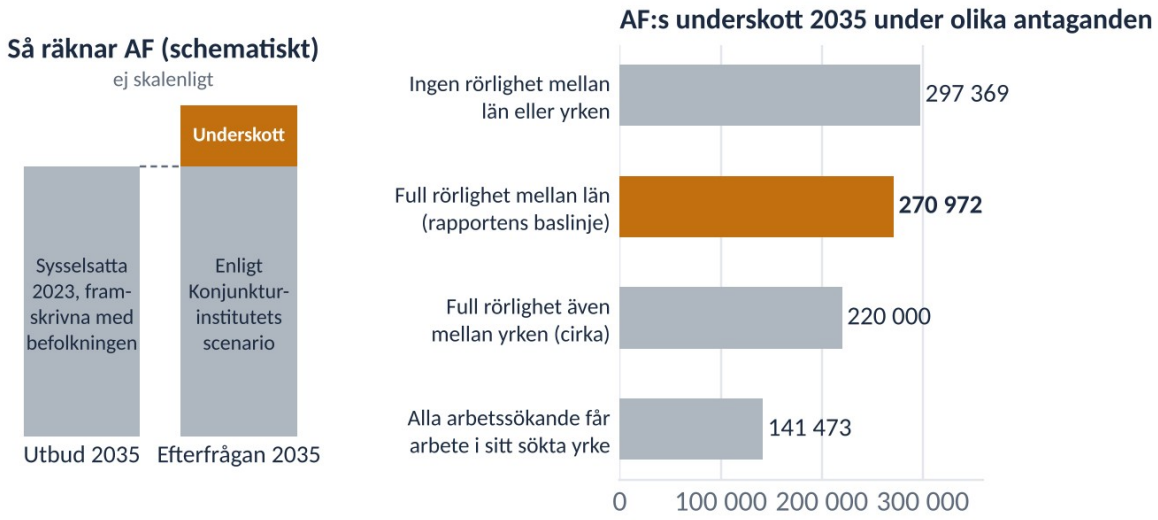


Figure 6. What the Swedish Public Employment Service's shortfall measures, and how large it becomes under different assumptions.

Source: K081 (pp. 9–11, 27) and K082. The left-hand part is schematic and not to scale; 220,000 is AF's own rounded figure.

Comparability with the investigation's baseline. AF calculates based on those employed in 2023, totalling 5,158,053 people including self-employed (K082). The investigation calculates based on employees in 2024, totalling 4,838,418 people (K062). Both are counts of people. The difference, around 320,000, is largely because self-employed people are included in AF's figure; it is largest in construction, agriculture, forestry and hairdressing occupations. The choice makes the investigation's calculation conservative: a smaller baseline gives less freed-up capacity. Section 6.5 shows the result using AF's own baseline.

2.2 Where the shortfall lies

The shortfall is concentrated. Care and health care (SSYK 22, 32 and 53) account for around 101,600 people, 37.5% of the entire shortfall. Next come casework and finance (around 39,600), trades, construction and

industry (around 37,800), and services and retail (around 35,300). Office, IT and expert occupations have little shortfall.

Table 2.1 shows the ten occupational groups with the largest shortfall. The right-hand column shows the shortfall as a share of today's employees in the group. That share is the same thing as the group's break-even (section 6.1): this is the share of the work that AI must take over for the group to cover its own shortfall.

Table 2.1 The ten occupational groups with the largest shortfall in 2035, according to AF (base scenario)

Occupational group (SSYK 2)	Shortfall 2035 (people)	Shortfall as share of employees 2024
53 Care occupations	68,036	11.6%
22 Occupations requiring advanced higher-education competence in health care	32,564	15.2%
33 Occupations requiring higher-education competence or equivalent in finance and administration	26,064	7.9%
71 Construction and civil-engineering occupations	19,301	10.3%
51 Service occupations	16,813	10.8%
41 Office assistants and secretaries	13,849	8.3%
24 Occupations requiring advanced higher-education competence in finance and administration	13,508	5.2%
26 Occupations requiring advanced higher-education competence in law, culture and social work, etc.	10,653	8.7%
52 Retail sales occupations, etc.	9,556	3.6%
15 Managers in health care and other public services	6,295	12.2%

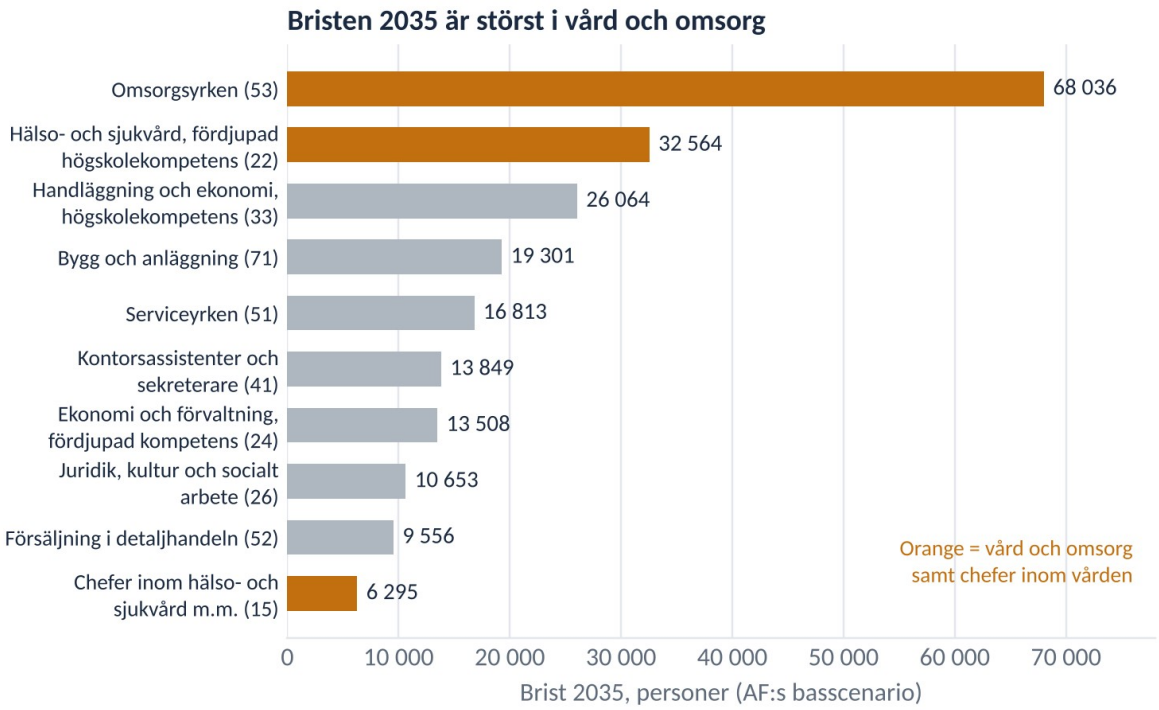


Figure 7. The ten occupational groups (SSYK 2) with the largest shortfall in 2035.

Source: K082, aggregated from SSYK 3 to SSYK 2; employees SCB Occupational Register 2024 (K062). Own processing.

2.3 The population: nearly stagnant, with growth coming from immigration

SCB's latest projection, Sweden's future population 2026–2070, published 2026-04-16 (K119), shows the following for the period 2025–2035:

Table 2.2 Population by age, 2025 and 2035 (K119)

Age group	2025	2035	Change
0–5 years	638,000	626,000	−12,000
6–15 years	1,238,000	1,055,000	−182,000
16–24 years	1,107,000	1,145,000	+38,000
25–69 years	5,938,000	6,034,000	+97,000
70–84 years	1,381,000	1,433,000	+52,000
85 years and older	304,000	483,000	+179,000

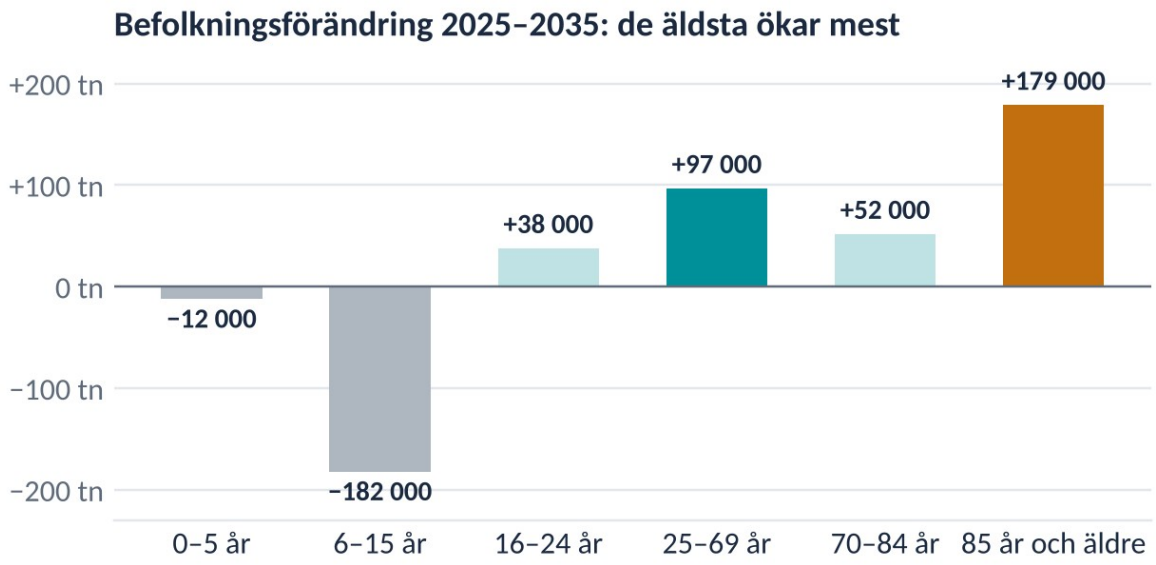


Figure 8. Change in population by age, 2025–2035.

Source: SCB, Sweden's future population 2026–2070 (K119).

- The population is expected to grow from 10.6 to 10.8 million by 2035. Over the period, deaths are expected to exceed births by around 30,000, and growth will come entirely from net immigration (around 200,000 over ten years). SCB assumes an average of around 80,000 people immigrate per year; this is immigration, not net immigration (K119).
- 97,500 children were born in 2025. SCB expects the number of births to be at its lowest in 2028, around 95,000 (K119).
- The outcome for 2025 was a population of 10,605,500 people on 31 December, an increase of around 17,800 (K113).

Two conclusions follow. **The population aged 25–69 is not shrinking in absolute numbers** – the 25–69 age group grows by around 97,000 – but it grows far less than the need, since the number of people over 85 increases by 179,000. The shortfall is therefore primarily a consequence of increased demand for care, not of there being fewer people of working age. And **a lower immigration outcome than SCB's assumption produces a larger shortfall**, since supply then grows less.

2.4 Sweden in international comparison

Sweden's population growth rests on immigration (K119). The same development, often stronger, is occurring in many other countries:

- According to the Global Burden of Disease study (GBD 2021, published in The Lancet 2024), fertility is expected to be below replacement level in 155 of 204 countries (76%) by 2050, and in 198 countries (97%) by 2100. Global fertility is expected to fall to 1.8 children per woman by 2050 and 1.6 by 2100; in Western Europe to 1.44 by 2050 (K122).

- China's population fell in 2025 for the fourth year running, by 3.39 million to 1.405 billion. Births were 7.92 million and deaths 11.31 million. The figures come from China's National Bureau of Statistics, as reported by Caixin (K123). The decline was 0.85 million in 2022, 2.08 million in 2023 and 1.39 million in 2024.

The labour shortfall is therefore not a Swedish peculiarity. The possibility of covering it through immigration is limited by the fact that the same development is occurring in many countries of origin. This makes the question of technology's role an international one, and the investigation's conclusions relevant beyond Sweden as well.

2.5 Other assessments of the need

- **SKR** reports, in “Välfärdens kompetensförsörjning 2023–2033” (K121), recruitment needs for municipalities and regions. SKR gives no combined figure; municipalities' need (288,500) and regions' (100,000) sum to around 388,500 (own summation). Recruitment need covers replacement for retirements and is therefore not comparable with AF's shortfall. SKR assesses that elderly-care staffing needs will grow by 65,600 people (+32%, from 204,000 to 270,000), and that half of the increase in the number employed in welfare is needed in elderly care. SKR also shows that shorter working hours increase staffing needs (pp. 48–49).
- **LO** (the Swedish Trade Union Confederation) has objected to the picture of a shrinking workforce. LO's working-time inquiry states that the share of the population of working age is expected to be larger in 2050 than today, and that Sweden's demographic development stands out positively compared with countries that have already shortened the working week (K162, p. 7). The objection is consistent with SCB's figures above on the number of people of working age. It is made in a context where LO argues for shorter working hours, and it says nothing about the fact that the need for care is growing faster than the workforce (section 2.3).

The investigation uses AF's assessment because it is the only one that covers the entire labour market by occupation and has a defined method. SKR's assessment shows that care is at the core of the shortfall.

2.6 What is not included in the baseline

- **Defence.** The defence sector's planned growth is not included in AF's base scenario in a way that can be separated out. The investigation reports AI efficiency gains in defence in the calculation (type T10) and defence's growth as a separate value outside the model (section 6.9).
- **Green transition.** Industrial investments in northern Sweden and electrification could increase labour demand beyond AF's assessment. No verified figure exists in the material.
- **Regional distribution.** The calculation is national. AF assumes full geographic mobility. In practice, the shortfall is larger in municipalities with declining and ageing populations, and the investigation's results do not apply directly to any individual municipality or region. Account therefore needs to be taken of the fact that the challenges can be substantial in certain parts of the country, both in terms of labour shortage and labour surplus based on the scenarios in this investigation.

3. Concepts and evidence principles

3.1 Generative AI and agentic AI

Generative AI in chat form (large language models) answers questions, writes and summarises when a person asks it to. The person still carries out the task, but AI makes the writing, summarising and analysis faster. **Agentic AI** itself plans and carries out tasks in several steps: it retrieves information, analyses it, makes sub-decisions within given rules, uses other systems, and hands over to a person where required. The difference is decisive for the labour market:

Table 3.1 Two ways AI affects work

	Augmentation (mainly generative AI)	Replacement (mainly agentic AI)
What happens	A person becomes faster or better at a task she still performs, for example because AI drafts text or analyses material	A process or process step is carried out by an agent; the person approves, handles exceptions and acts on what the agent flags
Effect on need	Fewer people needed for the same volume, if the time saved is used for other work	The role in the process is no longer needed, wholly or largely
Evidence today	Controlled studies exist, with mixed results (chapter 4.5)	Essentially only companies' and vendors' own claims (level 1)

Almost all existing measurement concerns augmentation. That no replacement effect is visible today is therefore weak evidence that it will not come. Today's studies, which analyse backward in time, mainly show that work is carried out faster and, in some industries, in greater volume, with roughly the same number of employees (chapter 4). This is the reason the investigation is built on scenarios.

3.2 What AI does in the work: analysis before administration

AI's greatest power lies in analysing large volumes of data and seeing patterns people do not see, and in acting or alerting based on them. Administration and documentation is the part that is easiest to introduce first, since it is rule-based and already digital. But it is not the most important effect. Three steps are linked:

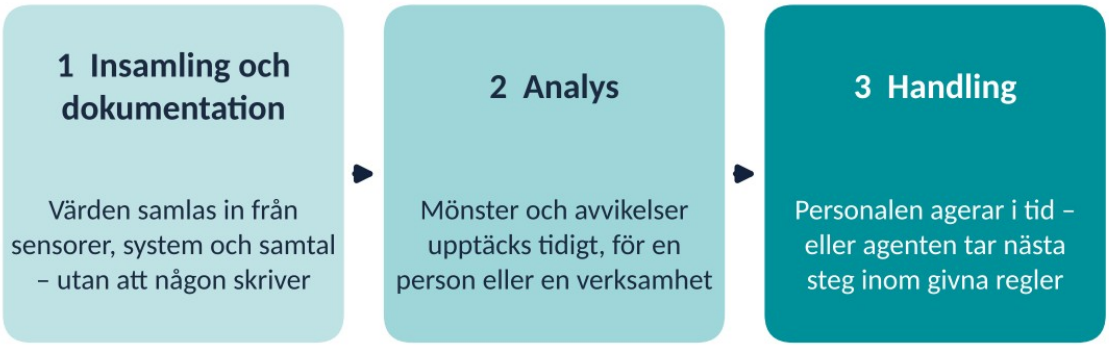


Figure 9. Collection, analysis and action: AI's greatest value lies in the analysis, not just in reducing administration.

1. Collection and documentation. Data is collected automatically, from sensors, systems or conversations, and documented without a person writing it. This frees up time directly.

2. Analysis. The data is analysed continuously and broadly, for a person or an entire operation. Deviations and patterns are detected earlier than with manual assessment.

3. Action. Staff act on what the analysis shows – administering medication, changing an intervention, ordering material, adjusting ventilation, preventing a problem – or the agent itself carries out the next step within given rules.

Examples from care show all three steps. Controlled studies of AI-assisted documentation show that doctors' documentation time decreases, but moderately: in a randomised study at UCLA with 238 doctors, time spent on chart notes fell by 9.5% with one of two tools, while the other showed no statistically significant effect (K151); another study shows 0.36 fewer hours of documentation per day and lower burnout (K152). In a randomised study across 13 US senior-living facilities (171 residents), a sensor system sent automatic alerts to nurses when movement, sleep or gait patterns changed. The comparison group declined functionally faster than the group with sensors; no difference in cost could be demonstrated (K153, level 3). A French pragmatic study of a system for early detection of decline in elderly people at home shows high accuracy (K154, level 2–3).

Other, smaller national pilot projects have shown larger effects, but they are neither documented nor carried out at sufficient scale to be classed as evidence. Isolated claims of 20–30% lower labour input have appeared, but lack a traceable source, sample and measurement method, and are reported here as an unconfirmed indication, not as evidence.

This means that AI in care does not primarily replace physical and relational work. It can free up time for it, and it can reduce the need for care by detecting decline earlier. The second effect – reduced care need through prevention – is not included in the calculation and, if it materialises, would strengthen the result. The same logic applies in many other occupations: caseworkers, economists, engineers and managers are affected mainly through analysis and decision support being produced by AI.

3.3 Levels of evidence

Table 3.2 Levels of evidence

Level	What it shows	Example
1 Supply/capacity	Someone offers, launches or can do something, or a company describes its own operations	A vendor launches agents; a benchmark of model capability; a company states that AI has replaced staff
2 Adoption	Something is used, measured in volume or frequency	Share of companies using AI (SCB, K120)
3 Outcome	Measurable effect of the use	Employment, productivity, cost in register data or experiments

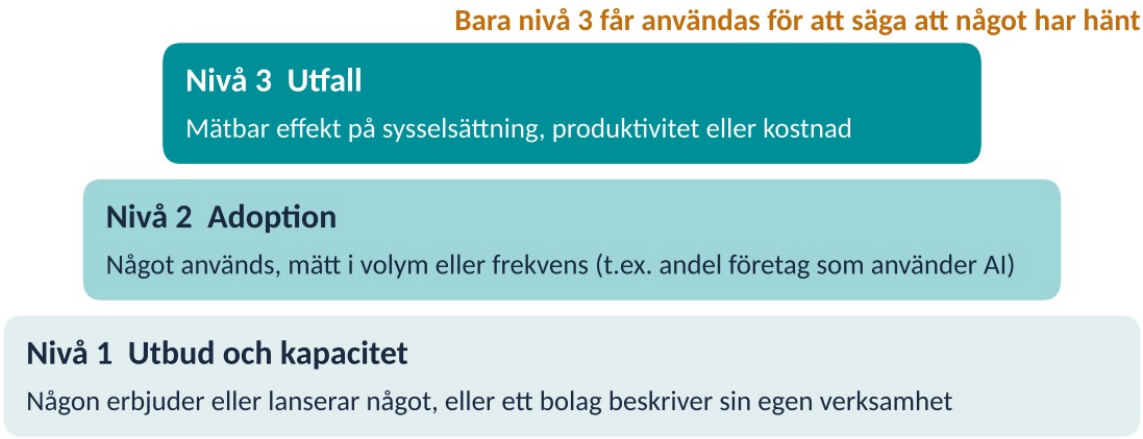


Figure 10. The investigation's three levels of evidence.

Five rules govern how the investigation draws conclusions:

1. Only level 3 may be used to say that something has happened.

2. A descriptive outcome is reported as observed, not as an effect of AI, if the study does not separate AI from other explanations.

3. A value is not extrapolated beyond the period and technology generation it measures.

4. Reference values that do not concern AI are used only in sensitivity analysis.

5. Commercial sources (vendors, consultants, analyst firms) are reported as perspective, never as supporting evidence.

3.4 Origin of values: source, reference or assumption

Every value in the calculation is labelled by where it comes from. The classification is the investigation's own. It corresponds to the usual distinction in model-based analysis between values taken from data, values borrowed from other contexts, and values that are assumed.

Table 3.3 Labelling of values

Label	Meaning	Example in the investigation
[Source]	The value is taken directly from a source in the register and used within the period it concerns.	Number of employees 2024 (SCB), shortfall 2035 (AF)
[Reference]	An empirical value that does not concern AI, for example a historical elasticity. Used only to show how sensitive the result is.	Demand price elasticity −0.7 (Nordhaus, K131)
[Assumption]	The author's judgement, justified and reported. All effect levels for agentic AI to 2035 are assumptions.	The percentages in table 5.1

3.5 Technology generation and historical comparison

Every source states which technology generation it measures: **before generative AI** (up to 2022), **generative AI in chat form** (2023–2026) or **agentic AI**. Most of the Swedish empirical evidence concerns the first two. A source from an earlier generation can show how the labour market has adapted before, but cannot support a forecast for agentic AI.

Agentic AI affects the entire labour market differently from most previous technology changes, since it can be used in almost all processes. The closest historical comparison is electricity, which in the research literature is used as an example of a general-purpose technology. Paul David (1990) showed that it took several decades before electrification showed up in productivity statistics, since factories first had to be rebuilt and work reorganised (K133). Brynjolfsson, Rock and Syverson (2021) describe the same pattern for AI: productivity may first be measured as lower, since companies invest in a transition that does not yet show up in statistics, and then rise (the "J-curve", K134). The comparison suggests the effect of agentic AI may be delayed and then arrive quickly.

3.6 Main mechanisms in the calculation

The occupational groups in the calculation are classified by how AI primarily affects the work (main mechanism). Each group can be affected in several ways; the main mechanism indicates what is assessed to weigh most heavily. The occupations below are examples, not a complete list (Appendix A has the full placement).

- **Mechanism 1 – analysis, decision support and casework.** AI can carry out large parts of the core task: analyse material, produce draft decisions, process cases and answer questions. Examples: office, casework, expert and managerial occupations.
- **Mechanism 2 – data collection, documentation and analysis supporting physical and relational work.** The core work is physical or relational and is carried out by people. AI collects and documents data, analyses it and shows what needs to be done, so more time goes to the core work and interventions can be made earlier. Examples: care, health care, services and parts of the trades.
- **Mechanism 3 – physical automation.** Robots or self-driving vehicles carry out the physical work. Requires robotics, not just software. Examples: vehicle drivers, warehousing, cleaning, parts of industry and defence.

4. What the empirical evidence shows

This chapter summarises what the material the investigation has reviewed can and cannot say. There are probably studies and data that have not been found, and the field is moving fast. The chapter deliberately ends without resolving the question of agentic AI: it shows where the evidence runs out, and why the rest of the investigation is built on scenarios.

4.1 Seven conclusions

The table summarises the chapter. The “What it means” column explains why the conclusion matters for the investigation.

Table 4.1 The chapter's conclusions

Conclusion	What it means	Evidence level
S1 No broad transformation of employment in the aggregate economy as of H1 2026.	What has happened so far is too small to show up across the whole economy. It does not rule out larger effects later.	3
S2 Labour-market entry has weakened for young people in AI-exposed fields of study and occupations since 2023.	The first visible effect comes through fewer new hires, not through employees being laid off.	3, descriptive
S3 How much of S2 is due to AI is not established.	The 2022–2023 interest-rate rises, a weaker economy and more graduates coincided with ChatGPT. No study has yet separated these explanations. This is the state of research, not a gap in the investigation's analysis.	3, open question
S4 No measurement shows that AI-driven cost reductions have led to lower prices and thus higher demanded volume.	Companies have not reported such effects so far. The author's assessment is that savings are primarily used to improve margins. This is decisive for volume compensation (chapter 7).	Lacking; judgement
S5 Measurements of earlier technology cannot support a forecast for agentic AI.	This applies both to studies before 2022 and to studies of early, general-purpose chat tools used without tailored rules, workflows and error control. Neither the absence of effects nor errors (“hallucinations”) in such tools can be carried straight over to agentic systems built for a bounded process.	Principle
S6 Adjustment so far happens via reduced new hiring, not layoffs.	The effect builds up slowly and shows first among young people and in job ads.	3
S7 For agentic AI there is as yet no outcome evidence; future effects are assumptions.	Agentic AI has not existed long enough for studies to be able to measure the effect (chapter 4.6).	Assumption

4.2 The government's and state inquiries' material

The government's AI strategy and the state inquiries (SOU) are not outcome studies, but they set out the state's picture of the situation and its goals. The investigation builds on them as follows:

Table 4.2 The government's and the inquiries' material

Document	What it says that is relevant here	Link to the investigation
Sweden's AI strategy, February 2026 (K004)	The goal is for Sweden to become one of the world's top ten AI nations and the best in the world at using AI in public administration. The strategy states that AI is reshaping job content, occupations and skills needs, that demographic change is welfare's great challenge, and that the transition should follow the Swedish model.	The investigation quantifies the strategy's two main questions – demographics and transition – against AF's shortfall. The goal for public administration aligns with the conclusion that AI needs to be directed at care (section 11.1).
The AI Commission's roadmap, SOU 2025:12 (K001)	Sweden is falling behind: in the Global AI Index, Sweden has dropped from 15th to 25th place. The Commission foresees a short-term labour-market imbalance and a need for an active labour-market policy. Smaller actors struggle to adopt AI.	Supports that the pace is slowed by adoption capacity (section 8.1) and that the transition is a central political question (section 11.2).
Privacy-enhancing technology in public administration, SOU 2026:44 (K005)	Modern privacy-enhancing technologies are used to a limited extent in public administration, mainly for exploratory purposes.	State source showing that public administration is still at an exploratory stage, with pilots rather than broad rollout.
Adapting to the AI Act, SOU 2025:101 (K002)	Proposes how the AI Act should be implemented in Sweden, with the Swedish Post and Telecom Authority as the main market-surveillance authority.	The regulatory framework is under construction, which affects the pace in the public sector (sections 8.6 and 9.5).

On why the effect is still small: beyond SOU 2026:44, the Riksbank notes that most Swedish companies are at an early stage of AI use (K085, section 4.3), and the UK government's evaluation of an AI tool in public administration found no productivity increase despite time savings (K126, section 4.5).

4.3 Swedish studies

The table shows the Swedish studies that measure outcomes or use. The “Limitations” column states why none of them alone can settle the question.

Table 4.3 Swedish studies

Source	Data and period	Main finding	Limitations
Growth Analysis (Tillväxtanalys) 2026:17, Nordström Skans & Sokolow Romin (K083)	Swedish Tax Agency monthly data and LISA register, Jan 2019–Jun 2026	No broad, rapid transformation. Employment grows in the most-exposed quarter. Staff turnover has fallen from 35% to 30% economy-wide, and by 7.5 points (from 31%) in the most-exposed segment. New graduates from the most-exposed fields have seen income growth about 20 points worse than the least-exposed (2018 vs. 2024 cohorts, p.26); no decline visible for lawyers. The share working at the most-exposed firms has fallen by about 8 points since Jan 2023.	Descriptive; does not establish cause. The firm-level analysis excludes care, education, public administration, finance and small firms.
Lodefalk, Löthman, Koch &	Job-vacancy portal and	The ratio of young (22–25) to	Under review (Economics

Engberg, "Same Storm, Different Boats" (K021), version 30 Sept 2026	monthly register data by employer and occupation, 2023 vs. 2024–2025	older employees fell 3.9 points more at high-AI-exposure employers. Departures rose; new hiring did not change significantly. Same magnitude for ages 26–30. Women −7.4%; no detectable change for men. The decline in postings since 2022 tracks interest-rate rises rather than ChatGPT.	Letters). The March version (Ratio WP 388) reported 5.5% with a different design. Sensitive to the exposure measure.
Engberg et al., Ratio WP 380 (K019)	Job-vacancy portal and register data, 2014–2022 (pre-generative AI)	Higher AI exposure was associated with more recruitment and slightly higher employment within the same firms.	Concerns the technology generation before ChatGPT. A contrast point, not a basis for forecasting.
Hellsten et al., IZA DP 18267 (K084)	Vinnova AI support 2019–2020 (up to SEK 500,000), 190 firms of which 53 received support	After five years, 24 points higher probability of advertising positions, especially AI roles (+19) and white-collar roles (+22.5). No statistically detectable change in employment.	Small sample; interpreted as augmentation and frictions rather than replacement. Pre-generative-AI.
Riksbank, Monetary Policy Report, March 2026 (K085)	Interviews with 41 firms employing about 270,000, 29 Jan–9 Feb 2026	Essentially all firms use some form of AI, but most are at an early stage and effects so far are relatively small. In some cases individual positions have been discontinued; the purpose is not to cut staff.	Interview-based; large firms. Does not capture whether firms have refrained from hiring they would otherwise have done.
SCB, "IT use in enterprises: AI 2025" (K120)	Firms with 10+ employees, 2021–2025	35.0% use AI in 2025 (25.1% in 2024, 10.4% in 2023). Small firms 30.8%, medium 49.6%, large 71.9%. 11.1% considered but refrained; of those, 74.7% cite a skills shortage.	Level 2. Measures use, not scale or effect; does not distinguish agentic AI from other AI. Time-series break.
Almega, "Three years with AI" (K023)	SCB data by industry since 2022	Information and communication: output +20.1%, employment +1.1%. Finance: employment +6%, output −2%.	Industry association report; does not separate AI from other explanations.

4.4 International studies

- **USA, Stanford (K022).** Employment for 22–25-year-olds in the most AI-exposed occupations was, in June 2026, about 19% below the comparison group, mainly through reduced hiring. The study is descriptive; the estimate halves when controlling for education.
- **Denmark (K066).** No effect on pay or hours two years after ChatGPT; work is reorganised before it shows up in pay and hours.
- **Finland (K124).** No youth effect, according to Kauhanen and Rouvinen (ETLA, January 2026). The difference between countries is itself a finding: institutions matter.
- **USA, Frank et al. (K012).** Unemployment risk in exposed occupations began rising already in 2022, before ChatGPT, which argues against AI as the sole explanation.

- **World Bank (K129).** 285 million job postings 2018–2025: postings in occupations where AI can replace the work were 12% lower than in other occupations, with the effect growing from 6% after one year to 14% after two and 18% after three.
- **Machine translation (K130).** Across 696 local US labour markets, a one-point increase in machine-translation use was associated with 0.7 points lower employment growth for translators.

Two caveats apply to all these studies. They use exposure measures from the same family, developed for the earlier technology generation, and are therefore less independent than they appear. And the cause of the decline among young people is not established (S3).

4.5 Effects within organisations

Studies of companies and public agencies show time savings for individuals, but small measurable effects at the organisational level. All concern generative AI.

- **Yotzov, Barrero et al., NBER w34836 (K097).** About 6,000 managers in the US, UK, Germany and Australia. 69% use AI, 1.5 hours per week on average. Over 90% report no effect on employment and 89% no effect on productivity over the past three years. Managers expect +1.4% productivity and −0.7% employment over the next three years. The methodologically strongest source in the material, but concerns generative AI.
- **Baslandze et al., NBER w34984 (K125).** About 750 managers: small aggregate employment effects in the short term; large firms expect to cut staff, small firms expect to grow; routine office roles are declining.
- **UK government evaluation of Microsoft 365 Copilot (K126).** 1,000 licences in public administration, autumn 2024. 72% were satisfied and some tasks went faster, but the evaluation found no evidence that the time savings led to higher productivity. Analysis work in Excel became slower and lower quality. The evaluation concerns an early version of Copilot.
- **Dillon, Jaffe, Immorlica & Stanton, NBER 33795 (K127).** Randomised trial with 7,137 employees across 66 firms over six months: about two fewer hours of email per week, but the same number of email threads, meetings and documents. The time saved did not translate into more work completed. The authors are Microsoft employees.
- **Brynjolfsson, Li & Raymond, QJE 2025 (K128).** 5,179 customer-service agents: +14% resolved cases per hour on average, +34% for new agents. The study does not address employment, but indicates likely future effects: the largest gains where experience is lowest.

4.6 Why agentic AI cannot yet be substantiated empirically

It is currently not possible to empirically substantiate the effect of agentic AI. The technology has not been in broad use long enough for register data and studies to measure it, and the time from data collection to publication is often 6–18 months. The investigation therefore uses the fragments that exist about generative AI: that it is used to quickly build simple solutions and pilots, for analysis, where language models are strong, and for text and illustrations. These show no massive effect today, since use is at an early stage.

A handful of companies nonetheless show where it can start. The US payments company Block stated in its Q4 2025 shareholder letter (26 February 2026) that it is reducing headcount from just over 10,000 to under 6,000. Over 4,000 people are being asked to leave or enter consultation. The company cites AI tools as the reason

(K106). This is the company's own statement (level 1), not an independent measurement. At 50 large banks, the number of employees working with AI has grown by over 25% in a year (K159, level 1–2). The author's assessment is that the effects will likely show up first in financial technology and banking [Assumption].

4.7 Evidence on agentic AI

Table 4.4 Evidence on agentic AI

Source	What it measures	Level	Use
UK government (K080), Jan 2026	16% of UK firms use AI, 7% agentic AI	2	The only adoption measure for agents the investigation has found. No Swedish equivalent has been found.
Gupta & Kumar (K069)	Exposure to agentic AI did not predict employment change 2023–2024 (ρ = −0.04)	3, null	The period precedes broad agent use.
METR (K068)	Doubling time for the length of tasks AI can handle: 196 days 2019–2025, 131 after 2023, 89 since 2024	1–2	A measure of how fast capability is growing.
Vendors (including Salesforce, ServiceNow, SAP, Epic)	Own customer cases and internal figures	1	Perspective, never evidence.

In the material the investigation has reviewed there is data on capacity, UK adoption data and vendors' own claims, but no outcome data and no Swedish adoption measurement for agentic AI, since the technology has not been available long enough for studies to substantiate the effect.

4.8 Companies' and vendors' claims

Vendors publish individual customer cases with high percentage figures, but in the material the investigation has reviewed there is no aggregated figure and no disclosure of sample, control group or measurement period. Figures that could not be traced to a primary source are not used.

Klarna is the most frequently cited case. The company stated in February 2024 that its AI assistant handled 2.3 million conversations in its first month, two-thirds of customer-service chats, and did work equivalent to 700 full-time employees (K135). In May 2025, the company's CEO told Bloomberg that cost had been weighted too heavily and quality had suffered; the company began hiring people for customer service again (K136, reported via a secondary source). The case is level 1 but illustrates that even realised replacement can create new need for people. It also concerns 2024, when language models had considerably lower capability than in 2026 (chapter 8.2).

4.9 Banks' own statements on staffing and AI

Several large banks have, since 2025, stated that headcount will fall, and some explicitly link this to AI. Table 4.5 summarises the banks' own plans and statements. This is level 1: companies' own statements about their own operations, not outcome measurements. The information comes from press releases, stock-exchange announcements and statements, not shareholder letters, and the plans often have several simultaneous reasons, such as cost savings and reorganisation.

Table 4.5 Banks' statements on staffing and AI (level 1)

Bank and date	What the bank states	K-ID	Source type
ABN Amro (Netherlands), 25 Nov 2025	Full-time positions to fall by a net 5,200 by 2028 vs. 2024, about half through natural attrition. Technology cited as central, including AI being built into processes.	K165	Bank press release
Nordea (Nordics), 17 Mar 2026	About 1,500 employees affected 2026–2027. The bank writes that, with Nordic scale and the effect of AI and process optimisation, it expects to have fewer employees in future than today.	K166	Stock-exchange announcement
Standard Chartered (UK), 19 May 2026	Roles in support functions to fall by more than 15% by 2030, and revenue per employee to rise by about 20% by 2028. Per Bloomberg, the bank had 52,271 employees in such functions at end-2025, equal to about 7,800 roles. The CEO described it as replacing staff with capital and AI, but said the next day the phrase had been taken out of context.	K167	Bank statement; Bloomberg and Alliance News (secondary)
JPMorgan Chase (USA), investor day 19 May 2025	The head of consumer banking stated that operations headcount is expected to fall by about 10% over the next five years, citing AI.	K168	Statement reported by Business Insider and eFinancialCareers (secondary)
Swedbank (Sweden), April 2026	550 full-time positions to be cut by end of 2027. The group CEO has said AI will primarily be used to grow business volume with existing staff, but that AI can lead to cuts where it is cheaper than staff.	K169	Reported by Dagens PS, citing SVT and ERR (secondary)
Morgan Stanley (USA), March 2026	About 2,500 positions, roughly 3% of staff, were cut. The bank cited business priorities, location and individual performance as reasons, not AI.	K170	Reuters and Wall Street Journal, reported by Invezz (secondary)
Bloomberg Intelligence (survey), Jan 2025	IT heads at 93 large banks expect, on average, a net 3% headcount reduction within three to five years, up to 200,000 positions globally; almost one in four expects 5–10%.	K171	Survey, reported by several outlets (secondary)

Sources: see K-IDs in the table and Appendix D. The figures are the companies' own plans and statements (level 1).

The table shows two things. Banking is the industry where the link between AI and fewer employees is now beginning to be stated openly. At the same time, companies in general are very reluctant to cite AI as a reason for forgone hiring or staff reductions. Morgan Stanley did not mention AI, and Danish trade unions report they have not seen members laid off with AI cited as the reason, even though several banks have mentioned AI in their statements (K172). Block (section 4.6) differs from the banks in the scale of the reduction, 40% of staff.

The author's assessment is that it will become more common during 2027 for companies to cite AI as a reason [Assumption]. This means the evidence available today is weaker than what would be needed to substantiate the effect.

4.10 Leading indicators

Since adjustment happens via new hiring, effects show up first among young people and new graduates, in job postings and in relative wages. Studies report that wages in AI-exposed occupations develop more weakly than in others (among others K009). This is a relative wage decline, not wage compression in the usual sense. The indicators are used in the monitoring (chapter 12), not in the calculation.

5. Method: how the scenarios are calculated

5.1 The question the calculation answers

How much does the need for labour fall by 2035 if the work in each occupational group can be carried out by fewer people with the help of AI, and is that enough to cover the shortfall AF calculates? The calculation gives a level for 2035, not a year-by-year path.

5.2 Step by step

1. Baseline. The number of employees in 2024 per occupational group (SSYK 2012, 2-digit level, 46 groups plus “occupation unknown”), totalling 4,838,418 people aged 16–69 [Source: K062].

2. Shortfall. AF's additional shortfall for 2035 per occupational group, summed from the 3-digit level, totalling 270,972 [Source: K082].

3. Type. Each occupational group is placed in one of ten impact types by main mechanism and assessed impact (table 5.1).

4. Reduced need. The type's percentage for Low, Mid and High is multiplied by the group's baseline [Assumption].

5. Coverage within the group. The part of the reduction that covers the group's own shortfall: the lesser of freed-up capacity and shortfall. What remains of the shortfall is called the remaining shortfall.

6. Surplus. The labour capacity freed up beyond the group's shortfall, and, nationally, that freed up beyond the entire shortfall. The surplus is expressed as a number of employees at today's average working hours.

7. Break-even. The average reduction required to cover the shortfall: shortfall divided by baseline, nationally and per group.

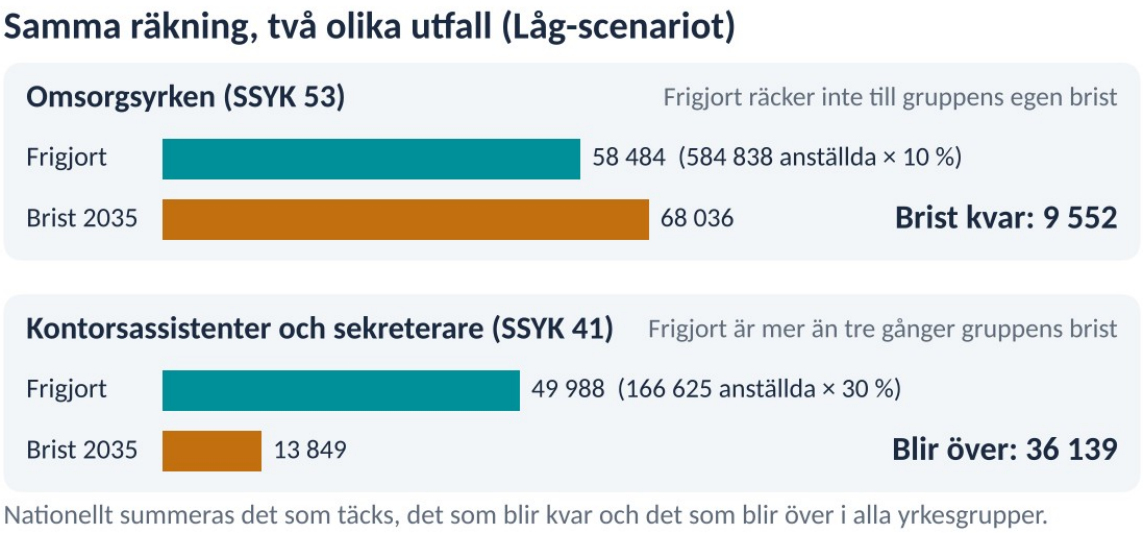


Figure 11. How the model calculates: the same calculation gives a remaining shortfall in care and a surplus in office occupations (Low scenario).

Source: Own calculation (Appendix B.1; K062, K082).

5.3 Impact types and scenarios

Low, Mid and High are three scenarios for how large the effect becomes by 2035. Low is a cautious assumption: AI spreads slowly and mainly augments existing work. Mid is a middle case. High assumes rapid spread, where agents take over entire process steps. The scenarios are not probability-weighted; no probability is assigned to any of them.

Table 5.1 Impact types and scenario values

Type	Name	Mechanism	Low/Mid/High (%) [Assumption]	SSYK groups
T1	Office support and customer service	1	30/40/50	41, 42, 44
T2	Casework, finance and administration	1	20/30/40	16, 24, 33
T3	Experts (analysis, technology, IT, law)	1	10/15/20	21, 25, 26, 31, 35
T4	Managers and leaders	1	10/15/30	11, 12, 13, 14, 15, 17
T5	Care and health care	2	10/20/25	22, 32, 53
T6	Education, culture and social work	1	10/15/20	23, 34
T7	Services, retail and security	2	5/10/15	51, 52, 54, 94, 95
T8	Trades, industry, warehousing and cleaning	2 and 3	5/10/15	43, 61, 62, 71–76, 81, 82, 91, 92, 93, 96
T9	Vehicle drivers	3	20/30/40	83
T10	Defence	3	5/10/20	01, 02, 03

The percentage states how much of the type's labour need in 2035 falls away at unchanged volume, compared with today's number of employees. The values are the author's assumptions, based on what the investigation has reviewed, together with discussions with people in various occupational groups. They rest on the author's judgement per occupational group, rounded to type level to avoid false precision. The rationale per type, with support and counter-support in the material and what would change the level, is in Appendix C. The “occupation unknown” group (19,522 people) receives 0%.

What the percentage includes. The percentage is the reduction actually achieved by 2035. It includes both what the technology can do and how far adoption has progressed. The obstacles in chapter 8 (adoption, regulation, costs, physical automation) are therefore already factored into the levels and should not be deducted again. This is also why Low, Mid and High differ: they describe different speeds of adoption, not different technology [Assumption].

Effect beyond normal productivity growth. AF's demand is based on the National Institute of Economic Research's base scenario, where productivity is already assumed to grow in line with historical patterns (K081, appendix p.30). The investigation's percentages therefore refer to the AI effect that comes on top of that

development [Assumption]. It cannot be determined how much of future normal productivity growth will come specifically through AI. To the extent it does, part of the effect is counted twice, and the calculation then overstates what is freed up. The uncertainty is greatest in the private sector; in publicly funded activities AF assumes low productivity growth.

Level of classification. The percentages are set per impact type and applied to 46 occupational groups (SSYK 2). This keeps the number of assumptions down, but a type can contain occupations that differ greatly. Type T5, for example, contains doctors, nurses, assistant nurses and childcare workers, and type T8 contains trades, industry, warehousing and cleaning. Section 6.5 therefore tests the result at AF's own level of detail, 147 occupational groups (SSYK 3), and Appendix B reports both levels.

5.4 Key choices and why

- No own demand growth (G = 0). AF's shortfall is already based on a growth assessment, and AF's appendix lacks demand by occupational group. Adding own growth on top would risk double-counting. The baseline is therefore today's number of employees. Since demand in 2035 is generally larger than today's employee count in the shortfall occupations, this choice gives a slightly too-low freed-up capacity in precisely those occupations. The author's original growth assumptions are reported as a sensitivity check (section 6.8).
- **Coverage per group instead of a flat matching share.** A freed-up caseworker does not automatically become an assistant nurse. By calculating coverage within each group, the calculation shows where the shortfall remains even when the national figure looks good.
- **Break-even as the main measure.** Break-even depends only on AF and SCB, not on the assumptions about AI. This makes it possible to state how large an effect is required without claiming how large it will be.
- Upper bound: no volume compensation in the main calculation. The calculation assumes lower costs do not lead to increased demand. This is the author's main assumption, not an established result (chapter 7). Compensation of 25%, 50% and 70% is reported as a sensitivity check.
- **Exposure measure as support, not rule.** The calculation shows AI exposure by occupation (the DAIOE index, Engberg et al.) to support the assessment. Exposure alone did not predict employment change 2023–2024 (K069) and therefore does not drive the percentage.
- **Linear path.** Where a time path is needed, the effect is assumed to grow evenly from 2024 to 2035. This is a simplification: real-world diffusion often follows an S-curve and can be delayed (sections 3.5 and 8).
- **Defence kept separate.** AI efficiency gains in defence are counted in T10; defence's planned growth is reported separately.

5.5 What the calculation does not do

- It does not calculate when the effect arrives, only the 2035 level.
- It does not account for new occupations or new tasks that AI creates; that is addressed in chapter 7.
- It does not account for early detection via AI reducing the actual need for care (sections 3.2 and 6.6). The calculation contains only the effect of the same care being delivered with less labour input.
- It assumes no mobility between occupations in the coverage measure. The national surplus measure assumes free mobility. Reality lies between the two.
- It is national and says nothing about individual municipalities or regions.

- It does not calculate value capture (who benefits from the savings); that is addressed in chapter 9.
- It does not account for people currently outside the workforce. The unemployed, underemployed and people far from the labour market can contribute to workforce supply, and AI can help through training, language support and adapted tasks. AF's calculation with perfect matching gives an order of magnitude (section 2.1), but no AI effect can be calculated for it.
- It does not distinguish between the private and public sectors. The same occupation receives the same percentage regardless of employer, even though the conditions for adoption differ (section 9.5). The results therefore cannot be read as a calculation for individual municipalities and regions.
- It does not calculate whether the transition is achievable in practice. Whether people can, want to and are able to change tasks, occupation and location depends on education, health, working environment, finances and geography. This is addressed in section 11.2 but is not included in the figures.

6. Results

6.1 Break-even: how large an effect is required

The 2035 shortfall is 270,972 people and the baseline is 4,838,418 employees. To cover the shortfall, labour demand needs to fall on average by 5.6%, provided the capacity freed up can be used in the occupations where the shortfall exists. Within AF's range of 200,000–300,000, break-even lies between 4.1% and 6.2%. Calculated on AF's own baseline, 5,158,053 employed in 2023, break-even is 5.3%.

How to read table 6.1. Break-even can also be calculated for each occupational group: the group's shortfall divided by the group's employees. This states how large a share of the work in the group AI must take over for the group to cover its own shortfall, without anyone changing occupation. The table compares break-even with the investigation's assumption in the three scenarios. If the assumption is lower than break-even, AI is not enough in that group, and shortfall remains unless people move there from other occupations. The table shows the eight groups with the largest shortfall relative to employees (among groups with a shortfall above 3,000).

Table 6.1 Occupational groups with the highest break-even

Occupational group	Employees 2024	Shortfall 2035	Break-even (shortfall/employees)	Assumption L/M/H (%)	Is the assumption enough? L/M/H
22 Advanced higher-ed. health-care occupations	213,771	32,564	15.2%	10/20/25	no/yes/yes
15 Managers in health care and other public services	51,675	6,295	12.2%	10/15/30	no/yes/yes
53 Care occupations	584,838	68,036	11.6%	10/20/25	no/yes/yes
51 Service occupations	156,322	16,813	10.8%	5/10/15	no/no/yes
71 Construction and civil-engineering occupations	186,898	19,301	10.3%	5/10/15	no/no/yes
74 Electrical and electronics installation/service	60,557	5,346	8.8%	5/10/15	no/yes/yes
26 Advanced higher-ed. law/culture/social-work occupations	122,303	10,653	8.7%	10/15/20	yes/yes/yes
41 Office assistants and secretaries	166,625	13,849	8.3%	30/40/50	yes/yes/yes

In Low, the assumption is not enough in six of the eight groups, and in Mid it is not enough for service occupations (51) and construction (71). The largest remaining shortfall in absolute numbers is in health care (22) and care (53), where the shortfall is large and the Low assumption (10%) is below break-even. This is why care is

tested separately in section 6.6. For managers in health care (15), the shortfall is small in absolute numbers (6,295).

6.2 Headline results

Table 6.2 shows the result for the entire labour market. Each row is explained in the right-hand column.

Table 6.2 Headline results 2035, no volume compensation (upper bound)

Measure	Low	Mid	High	What the measure shows
Reduced need, gross (people)	532,157	865,670	1,191,988	How many fewer people are needed in 2035 for the same work, summed across all occupations.
– as % of employees 2024	11.0%	17.9%	24.6%	The same, in percent. Compare with break-even 5.6%.
– vs. break-even (5.6%)	2.0×	3.2×	4.4×	How many times larger the effect is than what is needed to cover the shortfall.
Shortfall covered within same group (people)	223,132	268,575	270,943	The part of the shortfall covered without anyone changing occupation.
– as % of shortfall	82.3%	99.1%	100.0%	Share of AF's shortfall covered within the groups.
Shortfall remaining without mobility (people)	47,841	2,397	30	Shortfall that can only be covered if people change occupation (table 6.4).
National surplus, gross minus shortfall (people)	261,185	594,697	921,016	What remains if everyone freed up can move to where the shortfall is.
– as % of employees 2024	5.4%	12.3%	19.0%	The surplus relative to today's labour market.
– as % of population 2025	2.5%	5.6%	8.7%	The surplus relative to the entire population (10.6 million).
Freed up in groups with no remaining shortfall (people)	309,025	597,095	921,045	What remains if no one changes occupation.

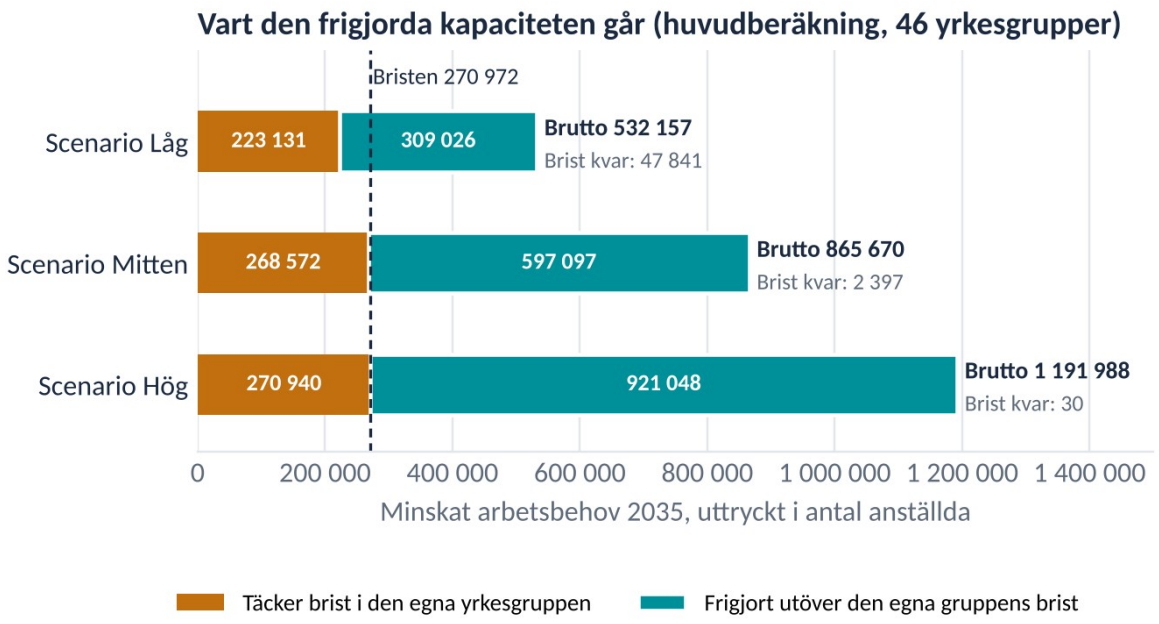


Figure 12. Where the freed-up capacity goes under the three scenarios.

Source: Own calculation (table 6.2).

Two measures of what remains are reported. National surplus (261,000, 595,000, 921,000) assumes everyone freed up can move to where the shortfall is. Freed up in groups with no remaining shortfall (309,000, 597,000, 921,000) assumes no one moves. The difference is largest in Low, where part of the shortfall remains in care at the same time as there is a surplus in other occupations. It is this remaining shortfall that makes occupational mobility a central question in Low.

What the surplus is and is not. The surplus is freed-up labour capacity: the part of labour demand that falls away beyond the shortfall, expressed as a number of employees at today's working hours. It is not a number of unemployed people. The capacity can be absorbed in several ways: vacancies not being refilled, natural attrition, mobility into shortfall occupations, new tasks, shorter working hours, or fewer people employed. The calculation says nothing about the split between these. Section 6.11 describes what is required for the surplus to become a real labour-market surplus.

6.3 Results by impact type

The table shows, for each type, how much is freed up in Mid, what share of everything freed up the type accounts for, and how much of the type's own shortfall is covered in Low and Mid.

Table 6.3 Results by impact type

Type	Employees	Shortfall	Freed up, Mid	Share of total freed up	Own shortfall covered, Low	Own shortfall covered, Mid
T1 Office support and customer service	259,237	17,735	103,695	12.0%	100%	100%

T2 Casework, finance and administration	594,817	39,572	178,445	20.6%	100%	100%
T3 Experts (analysis, technology, IT, law)	698,692	15,232	104,804	12.1%	100%	100%
T4 Managers and leaders	339,119	14,096	50,868	5.9%	92%	100%
T5 Care and health care	836,100	101,631	167,220	19.3%	80%	100%
T6 Education, culture and social work	386,078	4,743	57,912	6.7%	100%	100%
T7 Services, retail and security	575,658	35,345	57,566	6.6%	70%	97%
T8 Trades, industry, warehousing, cleaning	954,015	37,838	95,402	11.0%	62%	98%
T9 Vehicle drivers	161,206	2,908	48,362	5.6%	100%	100%
T10 Defence	13,974	1,872	1,397	0.2%	37%	68%

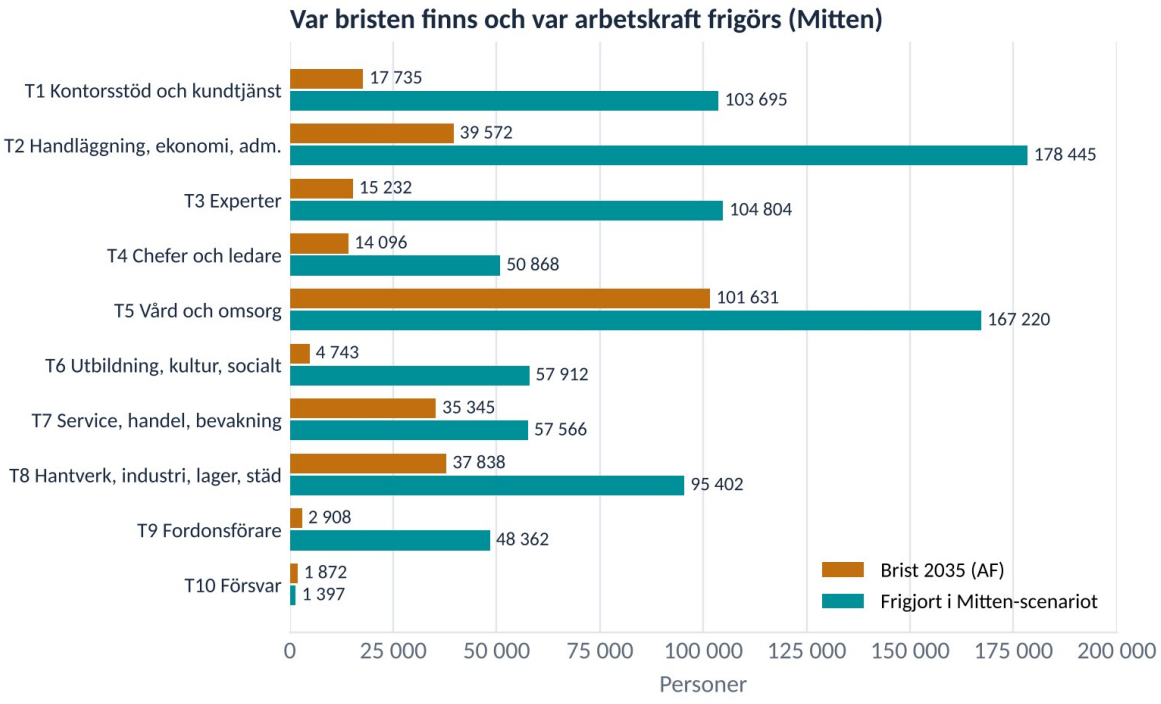


Figure 13. Shortfall in 2035 and freed-up labour in the Mid scenario, by impact type. The shortfall and the freeing-up occur in different parts of the labour market.

Source: Own calculation (table 6.3); shortfall per K082.

Casework and finance (T2) and care (T5) together account for about 40% of everything freed up in Mid. But they differ in one decisive respect: in T2 the shortfall is small and most becomes surplus; in T5 most of it goes to covering the type's own shortfall. Office support (T1), experts (T3) and vehicle drivers (T9) free up considerably more than their own shortfall.

6.4 Where the shortfall is not covered

How to read table 6.4. The table shows the occupational groups where AI does not free up enough within the group itself to cover its shortfall. “Remaining” is the group's shortfall minus what is freed up in the group in each scenario. The remaining shortfall can only be covered if people change occupation from groups with a surplus, or if the AI effect in the group turns out larger than assumed.

Table 6.4 Remaining shortfall without mobility between occupations

Occupational group	Shortfall 2035	Remaining, Low	Remaining, Mid	Break-even
22 Advanced higher-ed. health-care occupations	32,564	11,187	0	15.2%
71 Construction and civil-engineering occupations	19,301	9,956	611	10.3%
53 Care occupations	68,036	9,552	0	11.6%
51 Service occupations	16,813	8,996	1,180	10.8%
74 Electrical and electronics installation/service	5,346	2,318	0	8.8%
54 Other security occupations	3,548	1,315	0	7.9%
15 Managers in health care and other public services	6,295	1,127	0	12.2%
61 Agriculture and horticulture occupations	3,116	1,006	0	7.4%
91 Cleaning occupations	6,179	915	0	5.9%
02 Specialist officers	836	596	356	17.4%
01 Officers	462	354	246	21.4%
03 Soldiers etc.	574	224	0	8.2%
94 Fast-food, kitchen and restaurant staff etc.	5,396	112	0	5.1%
62 Forestry workers, fish farmers and fishers	350	106	0	7.2%
96 Recyclers, newspaper distributors and other service workers	2,552	60	0	5.1%
95 Market and street vendors	32	18	4	11.5%
Total		47,841	2,397	

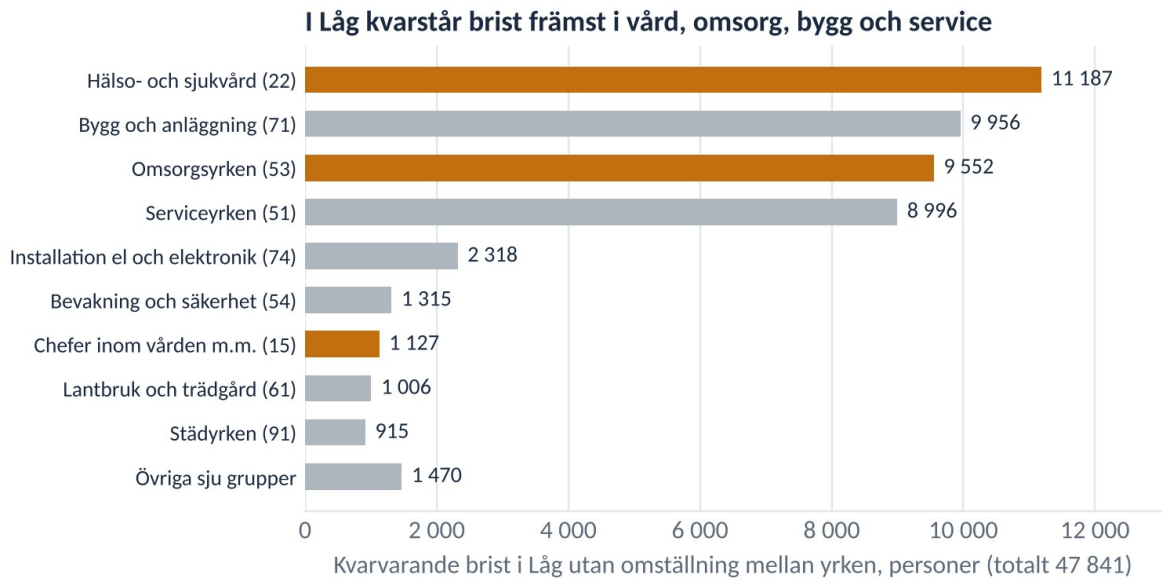


Figure 14. Remaining shortfall in the Low scenario by occupational group, if no mobility occurs between occupational groups.
Source: Own calculation (table 6.4 and Appendix B).

In Low, a shortfall of around 47,800 people remains, of which health care (22) about 11,200, construction (71) about 10,000, care occupations (53) about 9,600, and service occupations (51) about 9,000. In Mid, about 2,400 remains. AI therefore eases but does not solve the shortfall in care in Low, and the result is sensitive to the assumption: care's break-even is 11.6% and health care's 15.2%, while Low assumes 10%.

6.5 Check: finer occupational classification and AF's own baseline

The main calculation computes coverage within 46 occupational groups (SSYK 2). Within such a group it is thus assumed that someone freed up can take another occupation in the same group. AF calculates its shortfall across 147 occupational groups (SSYK 3) and without mobility between them. The same calculation, with the same percentages per impact type, is therefore repeated here at AF's level of detail. No new assumptions are introduced; the only thing that changes is how finely the shortfall and the freed-up capacity are matched. As a second check, AF's own baseline – employed in 2023 – is also used instead of employees in 2024 (section 2.1).

Table 6.5 Same assumptions, three ways of calculating coverage (own calculation)

Calculation	Shortfall covered (Low/Mid/High)	Shortfall remaining (Low/Mid/High)	Gross reduction (Low/Mid/High)	What it shows
Main calculation: 46 groups, employees 2024	82.3% / 99.1% / 100.0%	47,841 / 2,397 / 30	532,157 / 865,670 / 1,191,988	The investigation's headline result. Allows occupational change within an SSYK 2 group.
Check A: 147 groups, employees 2024	72.6% / 94.5% / 98.0%	~74,200 / ~14,900 / ~5,300	532,157 / 865,670 / 1,191,988	AF's own occupational level. No mobility between the 147 SSYK3 groups.
Check B: 147 groups, employed 2023 (AF's baseline)	75.7% / 96.2% / 99.1%	~65,900 / ~10,300 / ~2,600	565,525 / 921,464 / 1,267,097	Same as A, but with self-employed included, as with AF.

Source: Own calculation using employees by occupation (K062), AF's shortfall and employed by occupational group (K082), and the percentages in table 5.1. Nurses and specialist nurses (SSYK 222 and 223) are merged, as with AF.

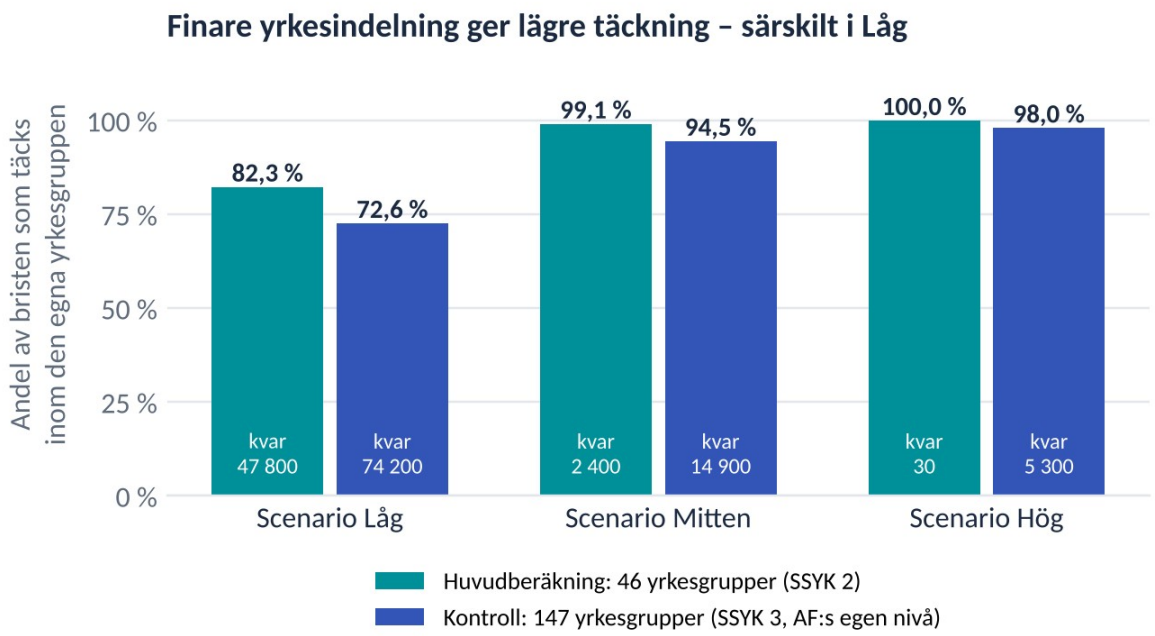


Figure 15. Share of the shortfall covered within the occupational group itself, at 46 vs. 147 occupational groups.
Source: Own calculation (table 6.5).

The gross reduction is the same in the main calculation and Check A, since the percentages are the same. The difference lies in coverage. At the finer level, 73% of the shortfall is covered in Low instead of 82%, and around 74,000 people of shortfall remain instead of 48,000. In Mid, 95% is covered instead of 99%. Break-even, 5.6%, and the national surplus are not affected.

Why the difference arises. The clearest example is care occupations.

Table 6.6 Occupational groups at SSYK 3 level with the largest remaining shortfall in Low (Check A)

Occupational group (SSYK 3)	Shortfall 2035	Remaining, Low	Remaining, Mid	Break-even
532 Assistant nurses	26,959	9,934	0	15.8%
333 Brokers etc.	15,752	9,021	5,656	46.8%
534 Care assistants and personal care workers etc.	26,611	8,051	0	14.3%
515 Facility and property caretakers	9,254	7,008	4,762	20.6%
711 Carpenters, bricklayers and construction workers	12,629	6,861	1,093	10.9%
222 Nurses	17,325	6,158	0	15.5%

533 Care workers (vårdbiträden)	12,783	3,848	0	14.3%
712 Roofers, floor layers and HVAC installers etc.	4,982	2,805	628	11.4%
221 Doctors	7,448	2,698	0	15.7%
741 Installation and industrial electricians etc.	4,759	2,183	0	9.2%
514 Beauty and body therapists	2,659	1,915	1,171	17.9%
227 Chiropractors, physiotherapists and occupational therapists etc.	3,542	1,334	0	16.0%
611 Crop growers in agriculture and horticulture	2,503	1,328	153	10.7%
541 Other security occupations	3,548	1,315	0	7.9%
Remaining 133 occupational groups	120,216	9,760	1,417	
Total	270,972	74,219	14,881	5.6%

Source: Own calculation (K062, K082). Break-even is shortfall divided by employees 2024. Totals differ by a few people from table 6.4 since AF's values are not whole numbers.

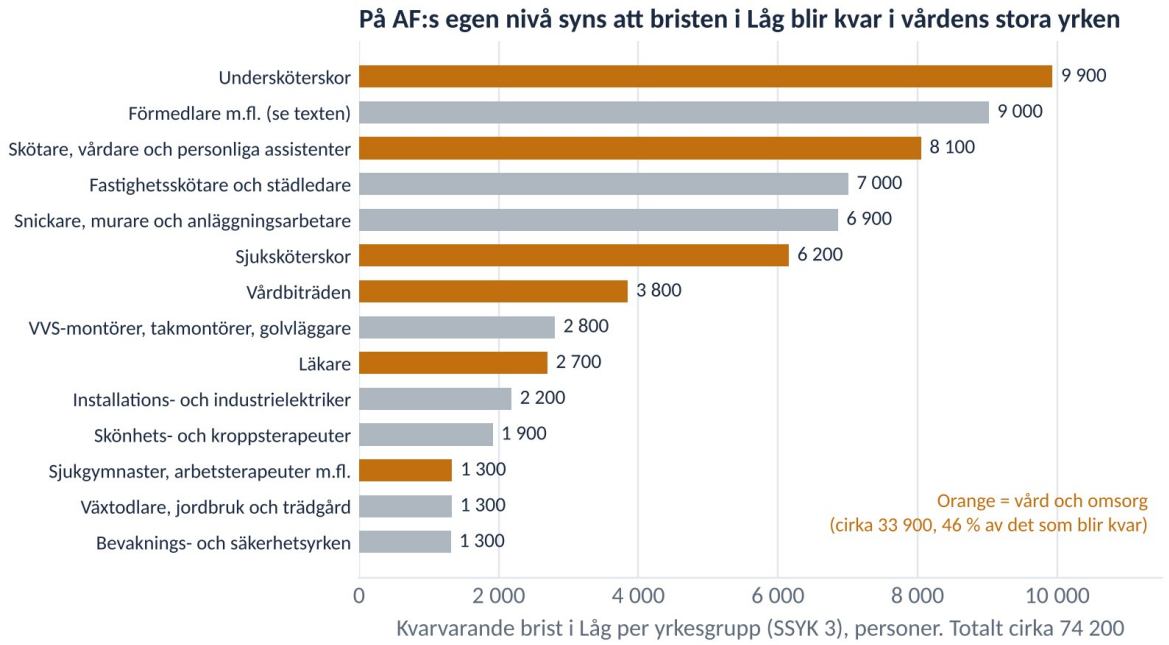


Figure 16. Remaining shortfall in Low by occupational group at SSYK 3 level.

Source: Own calculation (table 6.6 and Appendix B.2). Values rounded to the nearest hundred.

Three things are visible at the finer level. First: in Low, around 33,900 of the 74,200 remaining sits in care, mainly assistant nurses, care assistants and personal care workers, nurses, care workers and doctors. In all these occupations, break-even is 14–16%. The Low assumption (10%) is therefore not enough in any of care's major shortfall occupations, while the Mid assumption (20%) is enough in all of them. That result holds at both levels of detail and is treated as the robust finding.

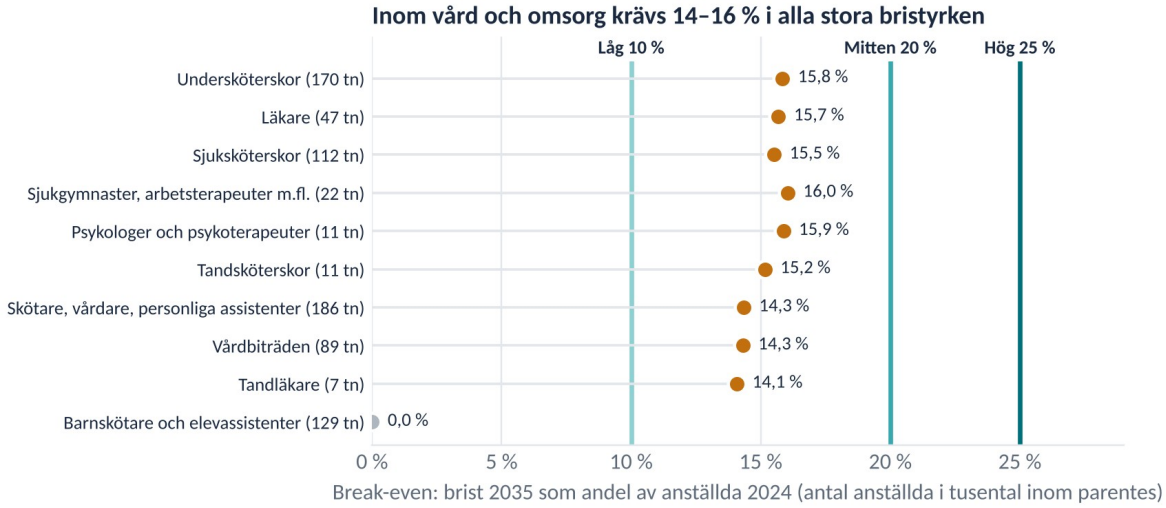


Figure 17. Break-even in care's occupational groups compared with the Low, Mid and High assumptions.
Source: Own calculation (Appendix B.2; K062, K082).

Second: in Mid and High, it is other occupations that remain, mainly brokers etc. (333), facility/property caretakers (515) and construction occupations (711, 712). The brokers group stands out: AF calculates a shortfall of 15,752 people in a group with 33,653 employees. The group includes, among others, employment-service officers, real-estate agents, property managers and freight forwarders. AF itself notes that individual occupational groups may be over- or underestimated (K081, p.25). The investigation has not been able to test the figure.

Third: with AF's own baseline (Check B), coverage is somewhat higher than in Check A, since self-employed are then included. The difference is largest in construction, agriculture and hairdressing occupations.

Conclusion of the check. The headline result holds in direction but not in level. That the aggregate effect is enough, that the shortfall remains in care, construction and services in Low, and that care covers its own shortfall in Mid, all hold at both levels. How much of the shortfall is covered without mobility depends, however, on how finely occupations are classified: 73–82% in Low and 95–99% in Mid. The finer level is closest to AF's own method. Appendix B reports the result by occupational group at both levels.

6.6 Special test: care (T5)

Care accounts for 37.5% of the shortfall but today has low AI use and much manual work. That could argue for either a low effect (hard to introduce, physical work) or a high one (large untapped potential, especially in

analysis and early detection, section 3.2). The 10/20/25% assumption therefore needs to be tested. The available evidence:

Table 6.7 Evidence on AI in care

Evidence	What it shows	Level	Argues for
UCLA randomised study, 238 doctors (K151)	Charting time −9.5% with one of two tools; the other showed no reliable effect; occasional errors	3	A low effect of documentation support alone
NEJM AI, Afshar et al. (K152)	0.36 fewer hours of documentation per day; lower burnout	3	A low-to-moderate effect
Finnish Ministry of Social Affairs and Health, 2024 survey (K118)	Doctors, nurses and social workers spend on average 3h 14m per day on documentation (self-reported)	Background	A large share of time that could be affected
Western Uusimaa wellbeing region, pilot (K155)	About 800 users over two years; users estimate 29 fewer minutes of documentation per day	2, self-assessed	A moderate effect
Rantz et al., sensor alarms in senior housing (K153)	Slower functional decline with automatic alarms on changed patterns; no demonstrated cost difference	3	An effect via analysis and prevention
Presage Care, France (K154)	Early detection of decline in elderly people at home with high accuracy	2–3	An effect via analysis
Helsingborg (K156), Kalmar (K157)	AI-documentation pilots in social services: 20 caseworkers per operation over six months (Helsingborg); speech-to-text project plan (Kalmar)	2, pilot	Low adoption today
Tandem Health on Eslöv (K158)	The vendor claims 59% shorter documentation time and three hours per day	1	A vendor claim, not evidence

Own calculation: if documentation takes around 3 hours of a working day and AI support reduces it by 10–50%, 18–90 minutes per day are freed up. The effect of analysis and early detection cannot be converted into staffing with today's evidence. Table 6.8 shows what a higher assumption would mean.

Table 6.8 Sensitivity to the assumption for care (own calculation)

Assumption T5 (Low/Mid/High)	Shortfall covered, Low	Shortfall remaining, Low	Shortfall covered, Mid
10/20/25% (current)	82.3%	47,841	99.1%
15/25/35%	89.8%	27,600	99.1%
20/30/40%	90.0%	27,102	99.1%

A higher assumption for care reduces the remaining shortfall in Low from around 48,000 to around 27,000. T5 alone cannot achieve more than that, since the remaining shortfall then sits mainly in construction (71) and services (51). The Mid column is the same across all three rows. That is not an error: under the current

assumption, the care shortfall is already fully covered in Mid, and the remaining shortfall in Mid, around 2,400 people, is in construction, services and defence (table 6.4).

The author's decision is to retain the 10/20/25% assumption. The controlled studies of documentation support support a low level, and the effect of analysis and early detection on staffing need has not yet been measured.

Two different effects in care. AI can affect care in two ways, and only one is included in the calculation. The first is that the same care can be delivered with less labour input, when documentation, planning and compilation are handled by AI. This is the effect the 10/20/25% percentage refers to. The second is that the actual need for care may fall, when continuously collected values are analysed and decline is detected early (section 3.2). This effect is not included, since it cannot be converted into staffing with today's evidence. The investigation thus describes analysis as AI's greatest power but calculates only the smaller part. If the second effect materialises, the care shortfall is smaller than AF's calculation, and the investigation's result for care is cautious. The effects around care need are described in the forthcoming investigation PHU02, which together with this investigation should give a more complete picture.

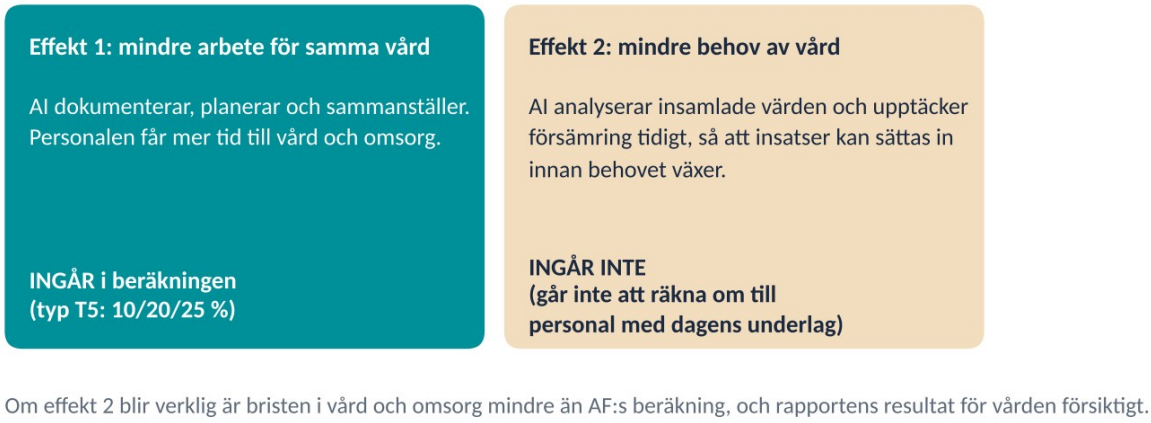


Figure 18. Two effects of AI in care. Only the first is included in the calculation.

At SSYK 3 level (section 6.5), a higher assumption for care gives a larger improvement than table 6.8 shows: with 15/25/35%, 84% of the shortfall in Low is covered instead of 73%, and with 20/30/40%, 85% is covered (own calculation).

6.7 Sensitivity: volume compensation

V is the share of the gross reduction that is offset by lower prices increasing demand. V = 0% means no new demand arises; V = 50% means half the reduction is absorbed by increased demand.

Table 6.9 Effect of volume compensation

Volume compensation V	Net Low	Net Mid	Net High	Covered Low	Covered Mid	Covered High
0% (main calculation)	532,157	865,670	1,191,988	82.3%	99.1%	100.0%
25%	429,672	705,535	965,551	77.8%	95.3%	99.9%
50%	327,187	545,401	739,114	71.6%	89.0%	95.6%

70%	245,200	417,293	557,965	63.7%	80.8%	87.2%

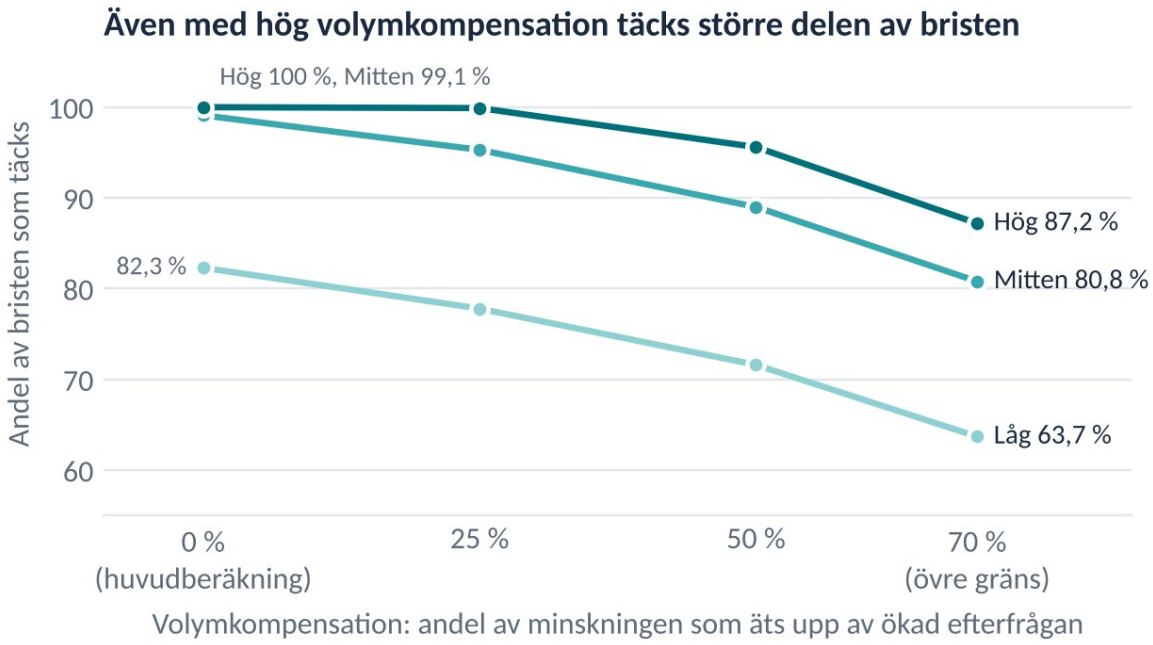


Figure 19. Share of the shortfall covered at different degrees of volume compensation.

Source: Own calculation (table 6.9).

V is applied only to types with market-driven demand; care and education are exempt, since demand there is governed by need and public decisions. Other activities with a large public share, for example defence (T10) or parts of IT and expert services (T3), are here treated as market-driven. The assumption is that the public sector, in most respects, follows the same efficiency pattern as the private sector, possibly with some lag, rather than standing entirely outside market logic. This is a simplification that is not separately verified and may need to be tested in a future revision. 70% is used as an upper bound: with a historical average price elasticity of around −0.7 (K131) [Reference], a price cut equal to the entire saving would produce a volume increase offsetting roughly 70% of the reduction (own simplified calculation). Even with 70% compensation, four-fifths of the shortfall in Mid is still covered.

There is also a reason compensation could be lower than historically. Increased demand through lower prices is a theory not established for AI. If AI simultaneously leads to higher unemployment, household purchasing power falls, and lower prices then meet a shrinking market rather than a growing one. This argues for low values of V [Assumption].

V captures only the first of the three compensating mechanisms in chapter 7: increased demand for the same service when the price falls. Increased demand elsewhere in the economy and new tasks are not included in the sensitivity analysis, since there is no basis for putting figures on them for AI.

6.8 Sensitivity: the author's own growth assumptions

If the author's original assumptions about demand growth without AI are used instead of G = 0, the gross reduction becomes 551,639, 901,048 and 1,239,020 people – that is, 19,000–47,000 more. The result is therefore not sensitive to this choice.

6.9 Defence

The AI efficiency gain in defence (T10) frees up around 700, 1,400 and 2,800 people. Defence's planned growth is reported separately: with the author's growth assumption (+20 to +30%), the net for the three occupational groups is an increase in need, to around 15,700 against 14,000 today in Mid (own calculation). Defence's growth therefore affects labour need in the opposite direction to the AI effect, and the area looks different from the rest of the labour market. How defence develops is also more uncertain than for other occupations.

6.10 How to read the results

- The figures are scenarios: what follows if the assumptions in table 5.1 hold. They are not forecasts.
- The robust result is break-even. That 5.6% is enough in aggregate follows from statistics, not from assumptions. Equally robust is that care's major shortfall occupations require 14–16%.
- The sensitive result is the distribution. The shortfall sits in occupations where AI mainly supports physical and relational work (mechanism 2), while the freeing-up happens in occupations where AI can take over core tasks (mechanism 1). How much of the shortfall is covered also depends on how finely occupations are classified (section 6.5).
- The gross figures are an upper bound, since no volume compensation and no new tasks are included.
- The surplus is freed-up labour capacity, not unemployment (sections 6.2 and 6.11).

6.11 Three states: shortage, imbalance and surplus

The results describe three different states of the labour market. They can coexist, and they require different measures.

- **State A – shortage.** Labour is lacking in certain occupations. AI can reduce the shortage. In Low, a shortage remains in care, construction and services.
- **State B – imbalance between occupations.** Labour capacity is sufficient in total, but it is freed up in occupations other than those with the shortage. This applies in all three scenarios. The state can persist for a long time, since mobility between occupations takes time and is not always possible.
- **State C – a real surplus.** Demand for labour falls even after mobility, new demand and new tasks. Only then do working hours, retirement age and the tax base become the central questions.

The calculation shows states A and B directly. State C does not follow directly from the surplus figures. For the freed-up capacity in Mid and High to become a real surplus, it must not be absorbed by mobility into shortfall occupations, by increased demand (chapter 7), or by new tasks. How much is absorbed cannot be calculated today. The surplus figures are therefore an upper bound for state C, and the measures in sections 11.3–11.6 are conditional on that state actually arising.



Figure 20. Three states of the labour market, what the calculation shows about them, and which measures belong to each.

7. Compensation and volume effects

Historically, automation has not led to durably fewer jobs in the economy as a whole. Three mechanisms have compensated: lower prices increase demand, savings increase demand in other sectors, and new tasks arise. This chapter goes through what is known about these mechanisms for AI, and why the main calculation nonetheless calculates without compensation.

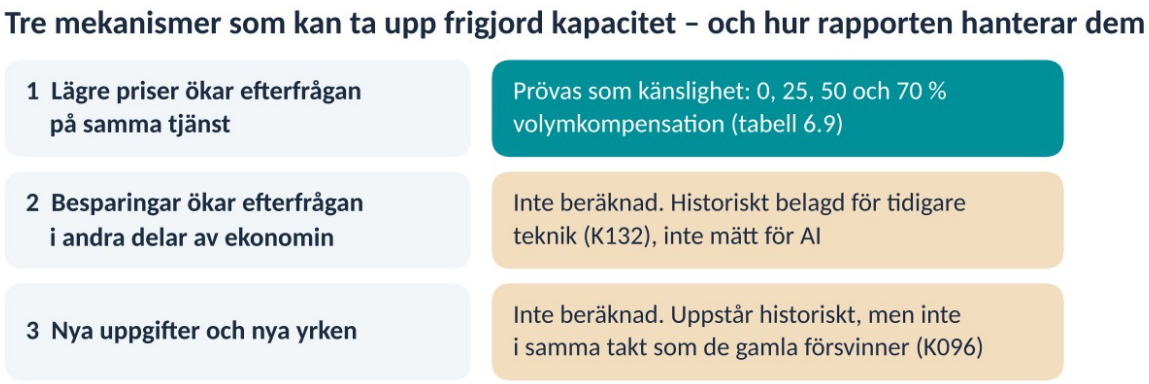


Figure 21. Three compensating mechanisms and how the investigation handles them.

7.1 Increased demand through lower prices

If AI lowers the cost of a service and the price falls, demand can increase enough that just as many, or more, people are needed. This is determined by the price sensitivity (elasticity) of demand. If demand is inelastic, labour need falls; if it is elastic, it can rise.

- Nordhaus (2006) estimates the average price elasticity of demand in the US economy at around −0.7, i.e. inelastic, and shows that the employment effect of productivity growth depends precisely on this (K131) [Reference].
- Autor & Salomons (2018), using data for 18 OECD countries and 28 industries since 1970, find that productivity growth has not reduced employment in the economy as a whole: losses in one's own industry have been offset by gains in other industries, but wages' share of income has fallen (K132) [Reference].

There is no AI-specific estimate of demand's price elasticity by sector. The AI-specific evidence that exists measures volume or employment and gives no support for compensation – if anything the opposite: time savings do not translate into more completed work (K127), job postings in exposed occupations are falling at an increasing rate (K129), and increased machine translation is associated with lower employment growth for translators (K130).

7.2 The author's assessment and how it is used

The author's main assumption is that volume compensation will be low: there is no general volume growth in society able to absorb freed-up labour, and buyers will demand that cost reductions be passed on as lower

prices within roughly three years at most, without that in itself creating equivalent new demand [Assumption]. There are signs such demands are already being made: Bain reports that customers of IT services firms are demanding around 20% efficiency gains on contract renewal (K140, level 1). The evidence is not sufficient to determine how large the compensation will be: there is no AI-specific measurement, and historical research shows that demand in other sectors and new tasks have offset earlier automation (K132, K096). The main calculation therefore uses V = 0% as an upper bound, not as a forecast, and 25%, 50% and 70% are reported as sensitivity (section 6.7). In the public sector, volume is governed by need and political decisions, not by prices, and no volume compensation is applied there.

7.3 New tasks and new occupations

Autor et al. (NBER WP 30389) show that most of today's US employment is in job titles that arose after 1940, but also that automation's demand-reducing effect has increased over the past four decades while augmentation's demand-increasing effect has not (K096) [Reference]. History thus shows that new tasks arise, but not that they arise at the same pace as old ones disappear.

New AI-related roles are growing quickly but from a low base. At 50 large banks, the number of employees working with AI has grown by over 25% in a year (K159). This is a gross figure; no source states how many new roles arise per role that disappears. Klarna's rehiring of people (section 4.8) shows that quality shortfalls can create new need for people even after realised replacement.

7.4 Indirect effects and timing

- **General-purpose technologies take time.** Electrification only showed up in productivity statistics once work had been reorganised, several decades after the technology existed (K133). Brynjolfsson, Rock and Syverson show that transition investment can first lower measured productivity before it rises (K134). For agentic AI this means that the absence of effects today says little about the 2035 level, and that effects in other sectors may arrive late.
- **The business cycle as a trigger.** Hershbein and Kahn show that US firms carried out routine-saving changes during the 2007–2009 recession, and that they persisted (K026) [Reference]. If this also holds for agentic AI, the effect could arrive earlier than the linear path assumes – for example, in a downturn.
- **Efficiency that does not show up in headcount.** Gains in capital tied up, energy or quality do not directly affect staffing need and are not included in the calculation.

7.5 Conclusion

The compensating mechanisms are real but unmeasured for AI. The investigation therefore uses an upper bound (V = 0) and shows how the result changes with compensation through lower prices. The other two mechanisms, demand in other sectors and new tasks, are not calculated. The conclusion that the aggregate effect is enough to cover the shortfall holds even with substantial compensation. The conclusion that care remains the largest shortfall category is not affected by volume compensation, since care specifically is exempt. The remaining shortfall in other occupational groups does, however, change with volume compensation. The conclusion about

the size of the surplus is, by contrast, the most uncertain in the investigation: the more that is compensated, the smaller the surplus.

8. Conditions and limiting factors

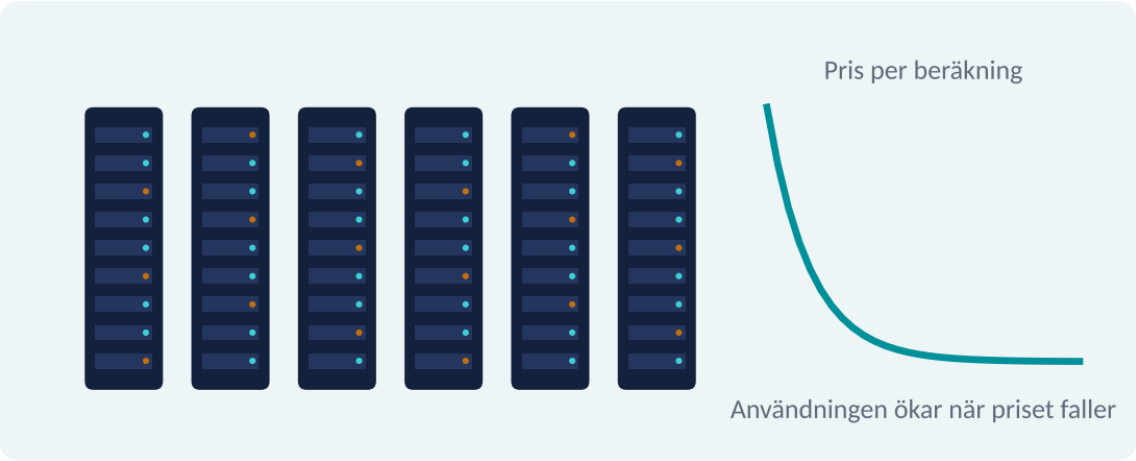


Figure 22. Compute capacity in data centres: as the price per computation falls, usage increases (illustration).

That the technology exists does not mean it is used. This chapter describes what could make the effect arrive later or turn out smaller than in the scenarios, and what argues for it going faster.

8.1 Adoption is the bottleneck

The consistent pattern in the material the investigation has reviewed is that the hard part is not the technology but getting it into workflows. Among Swedish firms that considered but refrained from AI, 74.7% cite a skills shortage as the reason (SCB, K120). The AI Commission notes that smaller actors struggle to adopt AI (K001), and public administration uses new technology mainly for exploratory purposes (K005). Most firms are at an early stage (K085).

This is not a contradiction of the investigation's assumptions, but it affects the pace. The scenarios state a level for 2035, and the linear path in chapter 5 is a simplification. If adoption is delayed, the effect may arrive later and faster, once workflows have been restructured (section 3.5). The author's assessment is that agentic AI began to be used during 2026; this is a judgement, not a measurement.

8.2 Capability is growing fast

The length of tasks AI models can handle has been doubling at an accelerating rate: every 196 days 2019–2025, every 131 days after 2023, and every 89 days since 2024 (METR, K068). This is a measure of capability (level 1–2), not of use. The exposure measures the evidence in chapter 4 relies on are fixed and show where capability stood when they were produced.

8.3 Cost per unit is falling, use is growing even faster

The price of using AI models has fallen very sharply. According to the Stanford AI Index, in November 2022 it cost around $20 to have a GPT-3.5-level model process a million tokens. By October 2024, the same

performance cost 7 cents. What cost 280 kronor therefore cost one krona not quite two years later (K027). Epoch AI shows prices have fallen at different rates for different tasks (K028). Google states that its per-unit cost of running its Gemini models fell by 78% during 2025 (K163, the company's own figure).

At the same time, use is growing even faster than the price is falling. Table 8.1 shows how some measures have developed at Google, one of the few companies that reports such figures on an ongoing basis. The measures are the company's own (level 2 for Google's services) and show the change over time, not just a level at one point.

Table 8.1 Price per unit and use: examples

Measure	Development	Source
Cost of using a GPT-3.5-level model	$20 → $0.07 per million tokens (Nov 2022–Oct 2024)	K027
Google's per-unit cost of running Gemini	−78% during 2025	K163
Tokens Google processes per month, all services	980 trillion (Jul 2025) → 1.3 quadrillion (Oct 2025); over 20× a year earlier	K141
Tokens per minute via Google's API to customers	7 billion (Oct 2025) → over 10 billion (Feb 2026)	K164, K163
Monthly users of the Gemini app	650 million (Oct 2025) → 750 million (Feb 2026)	K164, K163

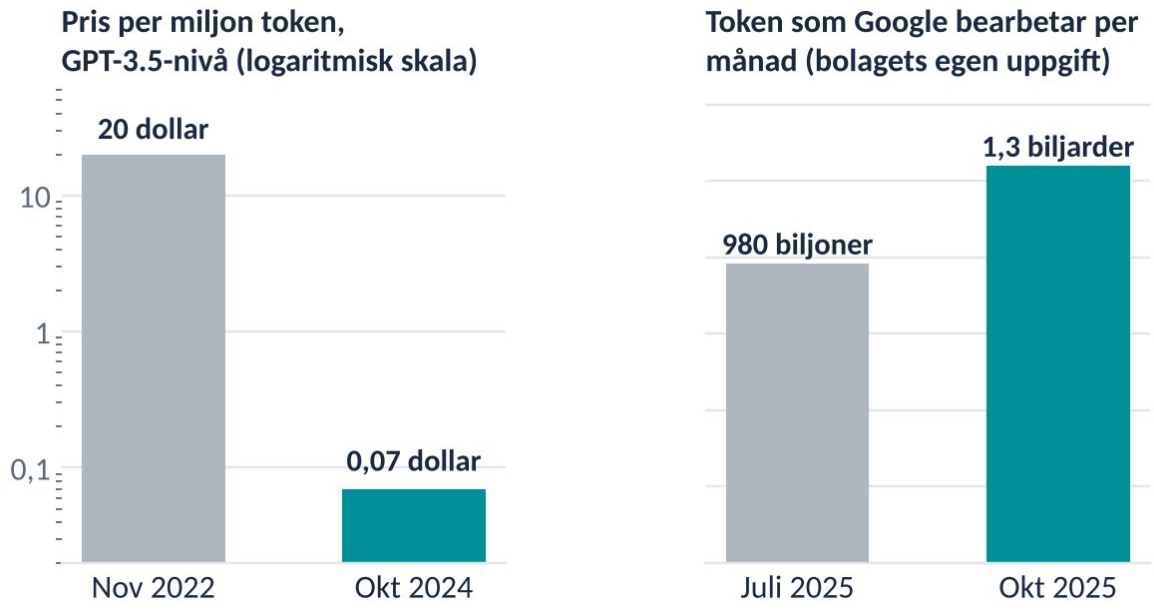


Figure 23. The price per unit is falling and use is increasing.

Source: Stanford AI Index (K027); Google, the company's own figures (K141, level 2 for Google's services).

The link between falling price and rapidly increasing use matters to the investigation for three reasons. First, a lower price per unit makes more tasks profitable to carry out with AI: tasks not worth automating at the old price become worth it at the new one. Second, agentic AI may require many model calls for a single task, since the agent plans, retrieves information, checks and redoes. Use can therefore grow much faster than the number of users. Third, total spending on compute capacity keeps rising even as the price per unit falls. This is why investment in data centres keeps growing (sections 8.7 and 9.3).

For an individual organisation, cost is hard to predict, since an agentic task can trigger many model calls. Cost uncertainty can make organisations hold back, but cost is not the main obstacle firms cite (K120).

8.4 Physical automation: humanoids and robots

As of mid-2026, humanoid robots are commercially proven only for narrow, repetitive material-handling tasks in structured environments such as warehouses and factories. Epoch AI assesses that robots are typically 3–10 times slower than humans and that the ability to generalise to new tasks is the biggest bottleneck (K039). Tesla's CEO admitted in January 2026 that the company's humanoids were not yet doing productive work (K040). China accounted for around 90% of the world's humanoid shipments in 2025 (K041, secondary source). Several robots are controlled in complex steps by remote operators (K043).

This supports the low assumptions for trades, industry, warehousing and cleaning (T8) and services (T7). Sweden has a high density of industrial robots but no leading humanoid manufacturer.

8.5 Self-driving vehicles

The assumption for vehicle drivers (T9, 20/30/40%) rests entirely on mechanism 3. According to the Swedish Transport Agency, trials of automated vehicles require a permit, and commercial traffic with fully driverless heavy trucks is not yet permitted in Sweden (K117). Regulatory development is ongoing nationally, in Europe and within the EU. The regulatory situation argues for slower rollout in Sweden and Europe than in the US. T9 is therefore the type whose assumption depends most on political decisions. At the same time, adoption could go very fast once the regulations are in place, since the technology will by then already be proven in countries that are further ahead [Assumption].

8.6 Regulation

The EU AI Act sets requirements for high-risk systems, including systems used in recruitment and workforce management. Through Regulation (EU) 2026/1744, the so-called Digital Omnibus Regulation, which entered into force on 27 July 2026, the deadlines have been pushed back: requirements for standalone high-risk systems apply from 2 December 2027, and for high-risk systems embedded in products from 2 August 2028 (K138). The new Machinery Regulation (EU) 2023/1230 applies from 20 January 2027 and covers machinery with embedded AI (K139). In Sweden, the Post and Telecom Authority is proposed as the main market-surveillance authority (K002).

In general, legislation is not keeping pace with AI development and is not positioned to, since lawmaking is a slower process than the very rapid AI development happening today. The postponement of the EU's requirements is one example. This is also why a debate is under way about temporarily halting or limiting development of the most advanced systems until regulation has caught up: the Future of Life Institute gathered signatures in 2023 for a pause in development of the largest models (K147), and in October 2025 published a call against developing superintelligence before it can be made safe, with over 65,000 signatures (K146). This points to a different challenge than in previous technology shifts. The lack of robust regulation for a technology that is global and spreading very fast through every part of every organisation is a serious problem. It can both slow the

pace, through uncertainty and future restrictions, and increase the risks if the technology spreads without control.

It can also create an imbalance between the private and public sectors. The public sector generally follows regulation more carefully than the private sector and may therefore lag in adopting agentic AI, thereby tying up tax funds in labour for longer than necessary [the author's assessment; see also section 9.5].

8.7 Data centres and compute capacity

Use requires compute capacity, and the build-out of data centres has become a political issue in both the US and Europe, since these are large projects affecting the local environment, power grids and land use. The organisation Data Center Watch has mapped local opposition in the US: projects worth $64 billion were blocked or delayed from 2023 to March 2025, and in Q2 2025 opposition concerned projects worth $98 billion (K144). In Ireland, where data centres used 22% of metered electricity in 2024, there was effectively a halt on new connections in the Dublin area 2021–2025, and the energy regulator decided in December 2025 on new conditions requiring data centres to contribute their own capacity (K145).

This creates a risk for adoption: if compute capacity is not built out, the pace could slow. At the same time, data centres compete for electricity with other industry and can crowd it out (section 9.6).

8.8 Summary

Table 8.2 Factors affecting the pace

Factor	Direction	Mainly affects
Adoption capacity and skills	Slows the pace	All types, especially the public sector and smaller firms
Rapidly growing model capability	Drives it forward	Mechanism 1
Falling price per unit	Drives it forward	All types
Robotics and humanoids	Slows until after 2030	T7, T8
Regulation of self-driving vehicles	Slows in Sweden	T9
Regulation lagging behind	Uncertain: can slow and increase risks	All types, especially the public sector
Compute capacity and local opposition to data centres	Can slow	All types
Investment pressure (section 9.3)	Drives it forward	All types

9. Value capture, financing and the tax base

The calculation in chapter 6 shows how much labour can be freed up. It says nothing about where the money goes. This chapter addresses that question. Beyond an illustration of the tax base in section 9.4, no values are set, since there is no basis for them.

9.1 Where the saving goes

When an agent performs work previously done by people, a saving arises for whoever uses the agent. The saving is distributed in four directions:

- **The vendor** of the model and platform takes a fee.
- **Customers** share in it through lower prices, if competition forces that.
- **The employer** retains some as margin.
- **Employees** who are replaced share in it only if there is transition support or shorter working hours; the share can be zero.

The distribution determines both the volume effect (chapter 7) and the tax base. The author's assessment is that buyers will, within roughly three years at most, demand that the saving be passed on as lower prices [Assumption]. That argues for the customer share becoming large over time, but not that it creates equivalent new demand for labour.

9.2 The value chain

Spending on AI is spread across several links – energy, chips, networking, cloud services, foundation models, operations and applications – but the margin is concentrated in chips and the largest models. A clear example is Nvidia, the largest supplier of AI chips: in fiscal year 2026 (through January 2026), revenue grew 65% to $215.9 billion, of which $193.7 billion from data centres, with a gross margin of 71.1% for the full year and 75.0% in Q4 (K143, the company's filing with the US financial regulator). The hardware chain is an external dependency for Sweden regardless of where operations run. Local hosting and open models retain more value nationally, but do not directly affect the number of hours worked.

The value chain can be broken into links (table 9.1). It is important to distinguish them, since they differ in where the value is captured and which countries have a realistic position.

Table 9.1 AI's value chain and where it sits today (simplified overview)

Link	What it is	Where it sits today
1 Energy	Electricity for data centres	Local. Sweden has good conditions, but data centres compete for electricity with other industry (section 9.6).
2 Chips	Design and manufacture of AI chips	Design of the leading AI chips happens mainly in the US (e.g. Nvidia, K143). A handful of manufacturers account for production.
3 Data centres and cloud	Compute capacity	Dominated by a handful of large cloud companies in the US and China. Alphabet alone plans $175–185 billion in investment

		in 2026 (K142).
4 Foundation models	Large language models	In 2024, 40 of the most significant models came from the US, 15 from China and 3 from all of Europe (K027).
5 Platforms and tools	Services built on foundation models, e.g. app-building tools	Spread across countries. This includes Swedish firms such as Lovable, built on others' foundation models; Google names Lovable among the customers of its Gemini models (K163).
6 Use (the agent layer)	Agents carrying out work for whoever uses them	Where the user is. This is where the saving arises (section 9.1).



Figure 24. AI's value chain in six links, and where Sweden can realistically capture value.

Source: Table 9.1 (K027, K142, K143) and the author's assessment in section 9.2.

Links 2–4 require capital at a scale only a handful of countries and companies have. Even large countries such as India lack capacity at the same scale: India's national AI initiative, the IndiaAI Mission, has a budget of 10,372 crore rupees, around $1.2 billion, over five years (K173, converted at the Riksbank's 2025 average rates, K175). That is less than a hundredth of what Alphabet alone plans to invest in 2026.

The author's assessment is that revenue in the chip, data-centre and model links will mainly accrue to the US and China [the author's assessment]. For Sweden, it is more realistic to capture value in use, in services built on foundation models, and in offering energy and sites for data centres, than to build a domestic equivalent to the largest model companies. This is no reason to forgo domestic applications, but it is a reason not to count on revenue from foundation models landing in Sweden.

9.3 Investment pressure

Investment in AI has no equivalent in previous technology shifts in speed and scale:

- The largest cloud companies plan investment in AI infrastructure of around $660–725 billion during 2026 (K051, a secondary source compiling the companies' own plans; level 1).
- Bain assesses that around $1,500 billion per year in infrastructure investment will be required by 2031, and that sustaining it requires a market of around $6,000 billion in annual revenue. Today's use cases – consumer, $200–400 billion, and enterprise, $1,000–1,400 billion – give $1,200–1,800 billion. The rest, around $4,200 billion, must come from new sources. Bain writes that trillions in new revenue are required, not just cost savings (K140, level 1, a forecast from a commercial analysis firm).
- For comparison: Swedish government spending in 2026 is projected at SEK 1,542 billion (K174). $1,500 billion converts, at the 2025 average rate of SEK 9.82 per dollar (K175), to around SEK 14,700 billion – nearly ten times the Swedish state budget, every year. Global car manufacturing turns over around $2,900 billion per year, according to the analysis firm IBISWorld (K176, a commercial estimate). The annual investment thus equals roughly half of global car manufacturing's turnover, and the revenue Bain says is needed is roughly twice the size of the entire car-manufacturing industry.

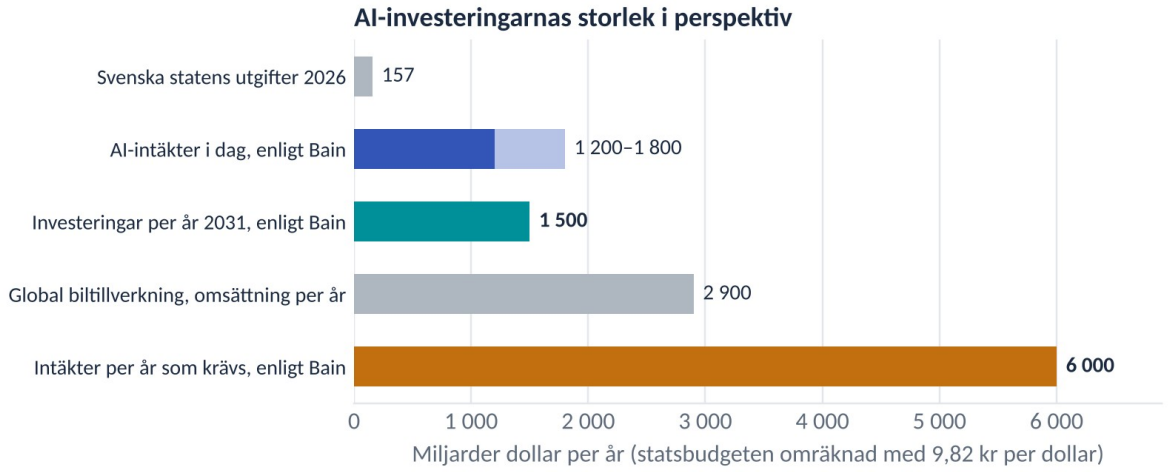


Figure 25. The scale of AI investment compared with government spending and global car manufacturing, $ billion per year.
Source: Bain (K140, level 1, forecast); government spending 2026 (K174) converted at SEK 9.82/USD (K175); IBISWorld (K176, commercial estimate).

- Depreciation on chips and data centres is large relative to industry revenue, and financing is increasingly done with debt (K052).

This creates strong pressure toward rapid development and adoption: investors need the technology used at scale, and vendors have strong reasons to push adoption in companies and the public sector. This is a reasonable basis for an explicit driver in the High scenario. It is not, however, evidence that the effect materialises. Bain places most of the missing revenue on new services and products rather than on replaced labour hours, so investment pressure alone is not a strong basis for large labour savings. If the revenue fails to materialise, a slowdown with write-downs is a possible outcome. That would lower the pace, but would likely

also have large effects on the economy as a whole, since the AI industry has become very large in a short time [the author's assessment].

9.4 The tax base

Taxes in Sweden rest heavily on labour. If hours worked are replaced by AI functions, the labour-based tax base shrinks, and the profit is often taxed where the vendor is domiciled rather than where the service is used. The investigation has not assessed how this should be handled, but the challenge is large. An illustration of the order of magnitude:

Table 9.2 Taxes on labour equal to the surplus, per year (illustration, own calculation; not a calculated tax shortfall)

	Low	Mid	High
Surplus after covered shortfall (people)	261,185	594,698	921,016
Wage sum (SEK 42,900/month × 12)	SEK 134bn	SEK 306bn	SEK 474bn
Employer contributions 31.42%	SEK 42bn	SEK 96bn	SEK 149bn
Income tax per tax table (SEK 9,111/month)	SEK 29bn	SEK 65bn	SEK 101bn
Total	SEK 71bn	SEK 161bn	SEK 250bn

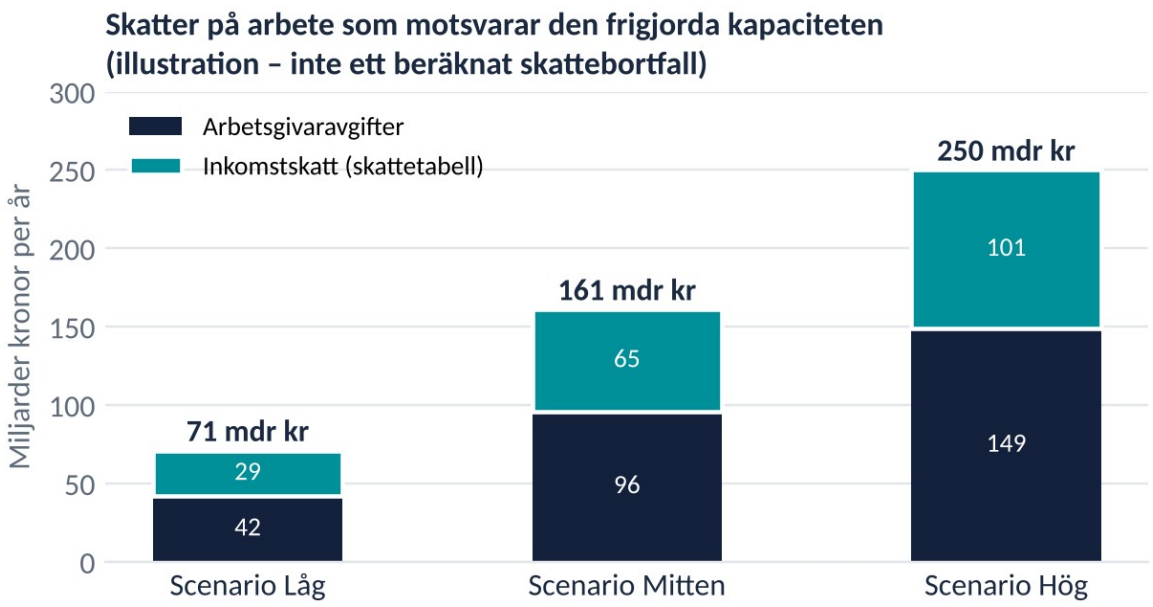


Figure 26. Taxes on labour equal to the surplus, SEK billion per year (illustration, own calculation; not a calculated tax shortfall).

Source: Own calculation (table 9.2), wages per K150, employer contributions per K149 and tax table 32 per K177.

The calculation uses the average monthly wage for the whole economy in 2025, SEK 42,900 (SCB, K150), and the full 2026 employer contribution rate, 31.42% (K149). Income tax is calculated using the Swedish Tax Agency's tax table 32 for 2026, column 1, which for a monthly wage of SEK 42,801–43,000 gives a tax deduction of SEK 9,111 (K177). Table 32 roughly corresponds to the average municipal tax rate in 2026, 32.38% (K148). The tax table

accounts for the basic allowance and the earned-income tax credit, and no state income tax applies at this wage. At an average wage, the employer contribution, SEK 13,479 per month, is therefore larger than the employee's income tax, SEK 9,111. Of the employer contribution, the old-age pension contribution, 10.21 percentage points, goes to the pension system; a shortfall therefore also reduces future pensions.

In High, the surplus corresponds to employer contributions and income tax of around SEK 250 billion per year. This is not a calculated tax shortfall. A shortfall only arises to the extent the surplus becomes fewer people employed. If the capacity is instead taken as shorter working hours at lower pay, as mobility into other occupations, or as increased output, the outcome differs, and those not working receive other income that is also taxed. The illustration also does not account for the surplus sitting in occupations with pay above or below average. The amount can be compared with total government spending in 2026 of SEK 1,542 billion (K174); income tax, however, mainly finances municipalities and regions, not the state. On top of this come effects that are not calculated: lower VAT if household consumption falls, and higher costs for benefits and transition support. The illustration shows the order of magnitude of the tax base affected if state C in section 6.11 materialises. The investigation does not address how a shortfall should be handled.

In the international debate, VAT is highlighted as the most robust domestic tax base; specific robot or AI taxes face objections regarding definitions and mobile capital (K053, K054, K055; analyses and opinion pieces, not measured effects).

9.5 The public sector

Different conditions apply in the public sector than in a market:

- Efficiency gains require investment in systems, data and skills before they produce savings. Municipalities and regions have limited capacity to invest.
- Volume is governed by need and political decisions. A saving does not become increased sales; it can be used to meet increased needs (which is precisely what the shortfall is about) or to lower costs. This requires politicians to have the skills and insight into what AI can and cannot do, and that skill is largely lacking today.
- Concern about regulation is greater in the public sector than the private sector. Data protection, confidentiality, the exercise of public authority and the new AI Act mean many operations are holding back. The risk is that tax money is used to retain manual work that could be done with AI, because it is uncertain how AI may and should be used – not because that is best for residents. In a time of labour shortage, this means tax funds are tied up in work that would be needed in care. [Assumption; the author's assessment]
- If AI leads to unemployment elsewhere in the economy, public costs for income support, labour-market measures and transition assistance rise, while tax revenue falls (section 9.4). These effects are not part of the investigation, but are noted for inclusion in a broader overall assessment.

The public sector thus accounts for both the largest shortfall and a significant share of the risk if the transition does not succeed.

9.6 Crowding-out: electricity, construction, land and skills

AI infrastructure competes for the same scarce resources as other electrification and infrastructure development: stable electrical capacity, construction capacity, grid-adjacent land, and occupational groups such

as electricians and grid engineers. Data centres account for around 12% of the Swedish national grid operator's (Svenska kraftnät) current connection requests (per parliamentary interpellation 2025/26:414, K056). Data centres require a great deal of electricity and can crowd out other industry. They are not labour-intensive to operate, and construction jobs are temporary, so they should not be counted as a contribution that solves the shortfall. The debate on data centres in the US and Europe is described in section 8.7.

The priority between market-driven allocation and political direction is a question of values the investigation does not answer.

10. Identified but unassessed problems

During the work, problems have been identified that could affect AI's impact on the labour market, or the ability to measure it, but which the calculation deliberately does not assess. The reason is usually that the pace is unknown, that the evidence is not enough for a figure, or that the question is an open policy area. That a problem is not assessed does not mean it lacks importance. The value chain, tax base and crowding-out are addressed in chapter 9; regulation and data centres in chapter 8.

Table 10.1 Identified but unassessed problems

Affects	Problem	Description	Trigger for reconsideration
Pace	Safety and governability	Incidents and weak regulation could both slow things down (pauses, oversight) and drive them forward (safety as a competitive advantage). The calls for a pause (section 8.6) show the question is live. No measurement of actual delay exists.	A documented pause at a major vendor; binding regulation of model access.
Pace	Cost predictability	See section 8.3. The problem is the variation in cost for an individual organisation, not the price level.	A shift to pricing per case resolved; clear acceleration after a period of restraint.
Distribution	Junior pipeline and skills supply	If routine tasks previously done by new hires are automated, the inflow of juniors falls, and seniors are later lacking. Whoever is to review AI's work needs experience built by doing the work. The evidence on young people (chapter 4) points this way but is descriptive.	A causal Swedish study that holds up to scrutiny.
Distribution	Offshored work	If agents replace work previously offshored, the effect does not show up in Swedish statistics. Conversely, remote operation of robots could move Swedish jobs abroad. A hypothesis.	Statistics distinguishing remotely operated from autonomous work.
Measurability	Evidence lag	The time from data collection to publication is often 6–18 months, in a field moving faster than that. The author must bridge the gap with judgement.	The source register is supplemented with data-collection period and publication date.
Measurability	The evidence measures the wrong phase	Almost all evidence measures augmentation (use of language models), while the question concerns replacement (agentic AI) (section 3.1).	The first independent studies of agentic replacement using register data.
Measurability	Hidden human labour and unstable job titles	“Autonomous” systems can involve remote operation (K043); new tasks are absorbed	Task-based statistics instead of title-based.

		into existing roles. Headcount by occupation code does not capture this.	
Other	Financial fragility in AI investment	Depreciation on chips and data centres is large relative to industry revenue (K052). A correction could slow the pace (section 9.3).	Write-downs, scaled-back investment plans, widening credit spreads.
Other	Preventive effect in care	Early detection via AI could reduce the actual need for care (section 3.2), but the effect on staffing need is unmeasured.	Swedish studies of care need before and after adoption.

Deliberately excluded: global capital flows from labour substitution (author's decision, 2026-08-15).

11. Courses of action

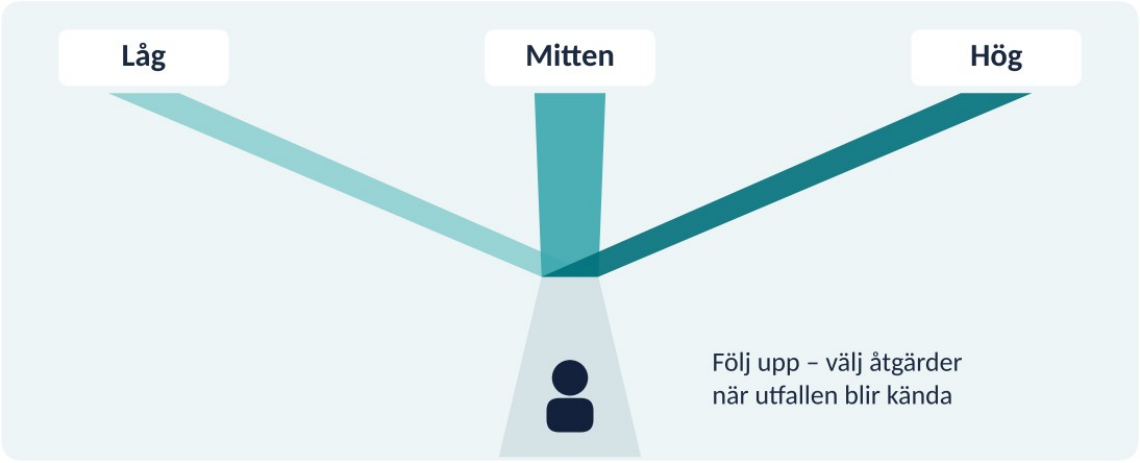


Figure 27. Three possible development paths; measures are chosen and scaled as outcomes become known (illustration).

Chapter 6 gives two main results that call for action. First: even when AI frees up enough labour capacity in aggregate, a shortfall remains in care in the Low scenario, since the freeing-up happens in other occupations (states A and B in section 6.11). Second: in Mid and High, capacity beyond the shortfall is freed up equal to 595,000 and 921,000 employees respectively, 12% and 19% of today's employees. If it is not absorbed some other way, a real surplus arises (state C). Sections 11.1–11.2 respond to the shortfall and the imbalance. Sections 11.3–11.6 respond to a surplus and apply only if it materialises. The courses of action are not recommendations throughout; where the author makes a judgement, this is stated.

11.1 Direct AI at the shortfall occupations

The most direct measure against the remaining shortfall is for AI adoption in care, health care and social services to proceed faster than average. This is in line with the AI strategy's goal that Sweden should be the best in the world at AI in public administration (K004). The greatest effect is likely to come from a combination of automatic documentation and ongoing analysis of collected data, so staff can act earlier (section 3.2). Documentation support alone gives a moderate effect according to the controlled studies (section 6.6).

- State and regional support for shared solutions for municipalities, which individually lack investment capacity.
- Shared measurement of time savings and care outcomes, so decisions can rest on outcomes rather than vendor claims.
- Swedish time studies for assistant nurses and nurses, where evidence is lacking.
- Clearer guidance on how the regulations may be applied, so uncertainty does not become a reason to hold back (section 9.5).

11.2 Mobility between occupations

The second route to the shortfall occupations is for people to change occupation. The author's assessment is that mobility and redeployment of staff between occupations and sectors will become even more important than today. The calculation shows that the freeing-up happens in office, casework and expert occupations, while the shortfall sits largely in care, health care and construction. The transition requires training, often at upper-secondary level (assistant nurse) or higher-education level (nurse), and takes years. It is also limited by the fact that not everyone wants to, or can, move into physically and relationally demanding occupations. The transition-support systems (transition study support, transition organisations) are built for individual transitions, not for moving tens of thousands of people between sectors. The AI Commission points to the need for an active labour-market policy (K001).

SKR's standing committee on workforce supply has, in its action plan “Kraftsamling för välfärdens kompetensförsörjning” (2024), identified three areas with the greatest potential to make use of existing staff's capacity and skills: health-promoting factors, full-time work and a longer working life, and early transition (K160). According to the action plan, the recruitment need in elderly care 2023–2033 could fall by around 8,100 people if part-time workers worked three more hours per week, and by around 15,000 if the average retirement age in elderly care rose from 64.2 to 66 (K160).

These measures are not linked to AI, but they act on the same shortfall the investigation addresses. They are especially needed if developments follow the Low scenario, where a shortfall remains in care. The investigation's reasoning on shorter working hours and the target retirement age in sections 11.3–11.4 concerns the parts of the labour market where a surplus arises, not the shortfall occupations. The investigation is part of the same effort: providing a basis for how workforce supply can be solved when labour is not sufficient.

Those outside the workforce. A third route is for more of those currently unemployed or underemployed to enter the shortfall occupations. AF's own calculation shows the order of magnitude: if all registered jobseekers could be employed in the occupation they are seeking, the 2035 shortfall falls from 270,972 to 141,473 people (K082). AF notes this is not fully realistic, since not all jobseekers have the skills in demand (K081, p.25). AI could ease the path in through training, language support and adapted tasks, but there is no basis for calculating the effect [Assumption].

Is the transition achievable? The calculation shows how large a transition would be needed, not whether it is possible. Someone freed up from an office or casework occupation must be able to, want to, and be allowed to start in another occupation, often involving physical and relational work, different pay and sometimes a different location. Education, health, working environment, financial conditions and geographic mobility determine how many do so. The same applies to employers: the private and public sectors have different conditions for adopting AI and for receiving those who make the transition (section 9.5). This is why state B, imbalance between occupations, can persist for a long time.

11.3 Managing a surplus: working hours

If a real surplus arises (state C in section 6.11) and is to be absorbed without the number employed falling, average working hours could be reduced. The arithmetic is simple: if total demand for hours worked falls by a given share and just as many people are to be employed, average working hours must fall by the same share.

Table 11.1 Surplus expressed as working time (illustration, own calculation)

	Low	Mid	High
Surplus after covered shortfall (people)	261,185	594,698	921,016
As % of employees 2024	5.4%	12.3%	19.0%
Equivalent reduction of a 40-hour week	~2 hrs	~5 hrs	~8 hrs

The illustration assumes full mobility between occupations and that the working-time reduction occurs where the surplus is. It also assumes all freed-up capacity becomes a real surplus, which is an upper bound. It shows the order of magnitude, not a plan. The reverse also applies: in shortfall occupations, a general reduction in working hours increases the shortfall (to do the same work in x% less time requires 1/(1−x) − 1 more people; 10% less time requires 11% more people). SKR shows the same for welfare services (K121, pp.48–49).

The author's assessment: it is reasonable to test a gradual introduction of shorter working hours, as the effects become measurable and in the parts of the labour market where the surplus arises [Assumption]. It cannot be implemented generally in the shortfall occupations until the shortfall is covered, or mobility between occupations works better than today, which is currently a major challenge.

11.4 Managing a surplus: retirement age

The pension system's target retirement age is 67 for those born 1960–1964, i.e. for retirements 2026–2031. The target age is linked to life expectancy and rises by around two-thirds of the increase in remaining life expectancy. The Swedish Pensions Agency's forecast is 68 for those born 1967–1981 and 69 for those born 1982–1997 (K137). Higher retirement ages increase labour supply. In a shortage situation this is desirable; in a surplus situation it reinforces the surplus.

The author's assessment: if developments follow the Mid or High scenario and a real surplus arises, the target age should not be raised at the pace current rules imply, but tested against how the labour market actually develops [Assumption]. The decision should be conditional on the indicators set out in chapter 12. In the Low scenario, a shortfall remains in care, health care, construction and services despite a national surplus of around 5% of employees, and there is then no reason to change the pace.

11.5 Skills and entry for young people

The clearest observed effect so far is that young people in AI-exposed occupations find it harder to enter (chapter 4). If junior roles disappear, the experience needed to review and lead AI-assisted work is threatened (chapter 10). This argues for:

- Education capacity following how demand actually changes, with particular attention to occupations where AF sees no shortfall while education provision is being expanded;
- Apprenticeship and trainee schemes where new hires do reviewing work under supervision;
- Prioritising the monitoring of new graduates' labour-market establishment (Growth Analysis, K083);
- Recognising that the scale of change the scenarios describe requires new skills-supply strategies across the entire labour market.

11.6 Financing and the tax base

If a larger share of the value accrues to capital and foreign vendors, the labour-based tax base shrinks. In High, the surplus corresponds to employer contributions and income tax of around SEK 250 billion per year, of which employer contributions around SEK 149 billion (chapter 9.4). This is the size of the tax base affected, not a calculated shortfall. On top of this come indirect effects, including on VAT. The investigation makes no proposal and does not address how a shortfall should be handled, but notes that the question needs to be examined before the effect grows large, and that the public sector bears both the largest shortfall and the increased costs if the transition fails.

11.7 How the measures interact

Table 11.2 Measures by scenario

Scenario	The shortfall	Surplus (capacity freed beyond the shortfall)	Key measures
Low	Partly remains in care, health care, construction, services	About 5% of employees nationally, while a shortfall simultaneously remains	Targeted AI in care; mobility; no changes to working hours or retirement age
Mid	Covered to 95–99% within the occupational groups	About 12% of employees	Mobility; test working hours in surplus occupations; reconsider the pace of the target age. The tax question becomes serious.
High	Covered to 98–100%, depending on classification	About 19% of employees	Working hours and retirement age become central; the financing and tax question becomes urgent



Figure 28. Key measures under each scenario.

Source: Table 11.2; surplus per table 6.2.

Since it cannot be known which scenario will occur, measures should be designed so they can be scaled up or down as outcomes become known. This is the reason for the monitoring model in chapter 12.

12. Monitoring and review

Since the calculation rests on assumptions, it must be reviewed as outcomes become measurable. The author proposes updating the calculation every six months.

12.1 What gets updated

- **The baseline,** when AF publishes a new analysis or SCB a new occupational register.
- **The types' percentages,** when outcome data for a type diverges from the linear path. Appendix C states, for each type, what annual change corresponds to Mid and what would change the level.
- **Volume compensation,** if AI-specific measurements of demand are published.

12.2 Indicators

Table 12.1 Indicators in both directions

Suggests a faster effect	Suggests a slower effect
Employment in the most-exposed quarter turns downward (Growth Analysis)	The income gap for new graduates levels off or shrinks
Staff turnover and departures increase in exposed occupations	The share of new graduates at exposed firms recovers
The effect on young people spreads to older age groups	Studies controlling for interest rates and the business cycle explain the effect away
SCB's measurement shows AI is used broadly and deeply, agentic AI included	The share of firms using AI plateaus (K120)
Employment in SSYK 41–42 and 33 falls in line with the Mid path	Employment in these occupations is unchanged for two years running
Investment and AI revenue develop in line with market forecasts	Investment plans are cut back, write-downs occur

Sources to monitor: Growth Analysis's ongoing monitoring, SCB's occupational register and IT-use-in-enterprises survey, AF's forecasts, the National Institute of Economic Research, Stanford's Canaries measurement and the UK government's adoption measurement, as well as new sources that begin tracking the question.

12.3 What is missing in Sweden

- A recurring measurement of agentic AI in Swedish companies and public operations (equivalent to the UK's, K080).
- Time studies and measurement of care outcomes in care, before and after AI adoption.
- Register data linking AI use at the employer level to employment.

13. Concluding synthesis

The investigation began with a question from the work on welfare's workforce supply: can agentic AI ease the labour shortage Sweden is heading toward? The answer has three parts.

In aggregate, it is enough. The 2035 shortfall equals 5.6% of today's employees. All three scenarios give a larger reduction in labour demand than that – 11%, 18% and 25%. The first figure follows from statistics. The scenarios are assumptions and should be reviewed as outcomes become measurable.

But the capacity is not freed up where the shortfall is. The shortfall sits in care, health care, construction and services, where the work is physical and relational and AI supports rather than takes over. The capacity is freed up in office, casework and expert occupations. In Low, 73–82% of the shortfall is covered without mobility, depending on how finely occupations are classified, and care's major shortfall occupations do not cover their own shortfall. In Mid, they do.

Sweden can therefore have a shortage and a surplus at the same time. This is the investigation's most important finding. AI changes not just how much work is needed, but where it is needed. Skills shortages in welfare and freed-up capacity in office occupations can coexist for a long time, unless people make the transition and AI is directed at where the shortfall is.

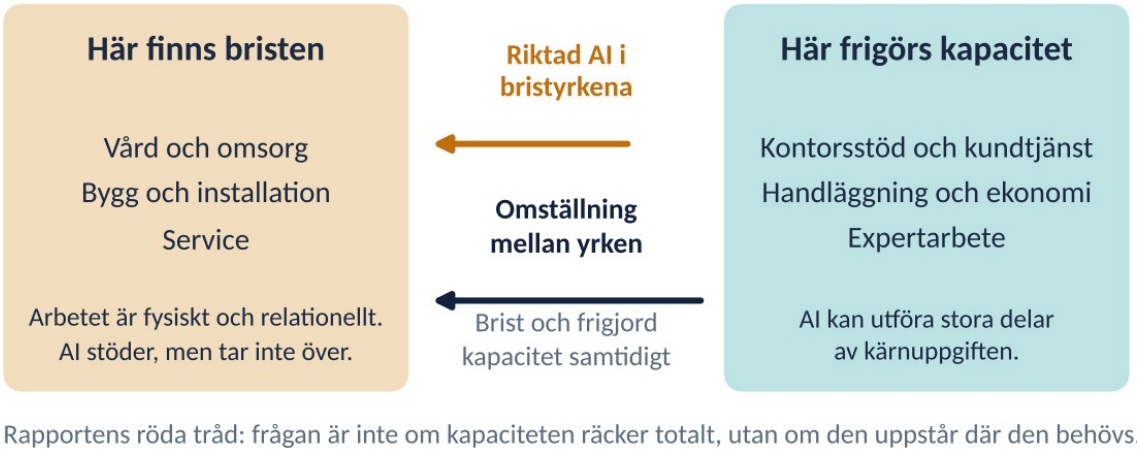


Figure 29. The investigation's thread: shortage and freed-up capacity arise in different parts of the labour market.

This implies an order for policy. First: direct AI at the shortfall occupations, especially care, and measure the effect. Then: make occupational mobility possible at a scale today's systems are not built for, and make use of those currently outside work. Only if the capacity is still not absorbed do working hours, retirement age and the tax base become the central questions. These questions need preparing now, since they take a long time to work through, but the decisions should be conditional on what the monitoring shows.

What the investigation cannot say is how fast this unfolds, how much of the freed-up capacity will be absorbed by new demand and new tasks, and whether the transition is achievable in practice. No one knows that today. The investigation is a first quantitative basis to build on and update, not a final answer.

Appendix A. Type table and placement of occupational groups

T1 Office support and customer service — main mechanism 1, Low/Mid/High 30/40/50%. 3 groups, 259,237 employees, shortfall 17,735.

- 41 Office assistants and secretaries
- 42 Customer service occupations
- 44 Other office and customer-service occupations

T2 Casework, finance and administration — main mechanism 1, Low/Mid/High 20/30/40%. 3 groups, 594,817 employees, shortfall 39,572.

- 16 Managers in banking, finance and insurance
- 24 Occupations requiring advanced-level tertiary education in economics and administration
- 33 Occupations requiring tertiary education or equivalent in economics and administration

T3 Experts (analysis, technology, IT, law) — main mechanism 1, Low/Mid/High 10/15/20%. 5 groups, 698,692 employees, shortfall 15,232.

- 21 Occupations requiring advanced-level tertiary education in science and engineering
- 25 Occupations requiring advanced-level tertiary education in IT
- 26 Occupations requiring advanced-level tertiary education in law, culture and social work, etc.
- 31 Occupations requiring tertiary education or equivalent in engineering
- 35 Occupations requiring tertiary education or equivalent in IT, sound and light engineering, etc.

T4 Managers and leaders — main mechanism 1, Low/Mid/High 10/15/30%. 6 groups, 339,119 employees, shortfall 14,096.

- 11 Politicians, senior officials and executives, etc.
- 12 Managers in finance, HR, marketing and sales and other administration, etc.
- 13 Managers in IT, logistics, R&D, property, construction and engineering and manufacturing, etc.
- 14 Managers in education
- 15 Managers in health care and other public services
- 17 Managers in other service industries

T5 Care and health care — main mechanism 2, Low/Mid/High 10/20/25%. 3 groups, 836,100 employees, shortfall 101,631.

- 22 Occupations requiring advanced-level tertiary education in health care
- 32 Occupations requiring tertiary education or equivalent in health care and laboratory work
- 53 Care occupations

T6 Education, culture and social work — main mechanism 1, Low/Mid/High 10/15/20%. 2 groups, 386,078 employees, shortfall 4,743.

- 23 Occupations requiring advanced-level tertiary education in teaching
- 34 Occupations requiring tertiary education or equivalent in culture, wellness and social work

T7 Service, retail and security — main mechanism 2, Low/Mid/High 5/10/15%. 5 groups, 575,658 employees, shortfall 35,345.

- 51 Service occupations
- 52 Retail sales occupations, etc.
- 54 Other security and protective service occupations
- 94 Fast-food workers, kitchen and restaurant assistants, etc.
- 95 Market and street vendors

T8 Crafts, manufacturing, warehousing and cleaning — main mechanism 2 and 3, Low/Mid/High 5/10/15%. 15 groups, 954,015 employees, shortfall 37,838.

- 43 Material-recording and transport-clerk occupations, etc.
- 61 Agricultural and horticultural occupations
- 62 Forestry workers, fish farmers and fishers
- 71 Building and civil-engineering occupations
- 72 Metal-trade and repair occupations
- 73 Precision, handicraft, craft-printing and related occupations
- 74 Electrical and electronics installation and repair occupations
- 75 Other craft and related occupations in wood and textiles, etc.
- 76 Food-processing craft occupations
- 81 Process and machine operators
- 82 Assemblers
- 91 Cleaners
- 92 Agricultural, forestry and fishery labourers, etc.
- 93 Other occupations in construction, manufacturing and goods handling
- 96 Refuse workers, newspaper deliverers and other service labourers

T9 Vehicle drivers — main mechanism 3, Low/Mid/High 20/30/40%. 1 groups, 161,206 employees, shortfall 2,908.

- 83 Transport and machine-operator occupations

T10 Defence — main mechanism 3, Low/Mid/High 5/10/20%. 3 groups, 13,974 employees, shortfall 1,872.

- 01 Officers
- 02 Specialist officers
- 03 Soldiers, etc.

Occupation unknown (SSYK 00, 19,522 employees) is included in the baseline at 0%.

Appendix B. Results by occupational group (SSYK 2-digit and 3-digit)

B.1 The main calculation: 46 occupational groups (SSYK 2-digit). Columns: employees 2024 (SCB, K062), exposure to generative AI (DAIOE, weighted percentile 0–100; missing for military occupations), 2035 shortfall (AF base scenario, K082), break-even (shortfall divided by employees), freed up in Mid (employees × the type's percentage in Mid), and covered shortfall in Low and Mid (the smaller of freed-up and shortfall).

SSYK	Occupational group	Type	Empl.	Expo.	Shortfall	B-E	Freed M	Cov. L	Cov. M
01	Officers	T10	2,161	—	462	21.4%	216	108	216
02	Specialist officers	T10	4,803	—	836	17.4%	480	240	480
03	Soldiers, etc.	T10	7,010	—	574	8.2%	701	350	574
11	Politicians, chief executives and senior officials, etc.	T4	24,466	65	447	1.8%	3,670	447	447
12	Managers in finance, HR, marketing, sales and other administratio n, etc.	T4	116,641	79	2,689	2.3%	17,496	2,689	2,689
13	Managers in IT, logistics, R&D, property, construction and engineering and manufacturin g, etc.	T4	96,656	67	3,243	3.4%	14,498	3,243	3,243
14	Managers in education	T4	17,911	65	15	0.1%	2,687	15	15
15	Managers in health care and other public services	T4	51,675	68	6,295	12.2%	7,751	5,168	6,295
16	Managers in banking, finance and insurance	T2	5,851	70	0	0.0%	1,755	0	0
17	Managers in other service industries	T4	31,770	48	1,407	4.4%	4,766	1,407	1,407
21	Science and engineering professionals (advanced-level)	T3	188,784	89	2,359	1.2%	28,318	2,359	2,359
22	Health-care professionals (advanced-level)	T5	213,771	47	32,564	15.2%	42,754	21,377	32,564
23	Teaching professionals (advanced-level)	T6	309,363	72	0	0.0%	46,404	0	0
24	Economics and administratio	T2	259,200	92	13,508	5.2%	77,760	13,508	13,508

	n professionals (advanced-level)								
25	IT professionals (advanced-level)	T3	180,127	98	0	0.0%	27,019	0	0
26	Legal, social and cultural professionals (advanced-level)	T3	122,303	68	10,653	8.7%	18,345	10,653	10,653
31	Engineering associate professionals	T3	153,392	50	1,503	1.0%	23,009	1,503	1,503
32	Health associate professionals and laboratory technicians	T5	37,491	46	1,031	2.8%	7,498	1,031	1,031
33	Economics and administration associate professionals	T2	329,766	73	26,064	7.9%	98,930	26,064	26,064
34	Culture, wellness and social-work associate professionals	T6	76,715	45	4,743	6.2%	11,507	4,743	4,743
35	ICT, sound and light technician associate professionals	T3	54,086	74	717	1.3%	8,113	717	717
41	Office assistants and secretaries	T1	166,625	89	13,849	8.3%	66,650	13,849	13,849
42	Customer service occupations	T1	72,055	76	3,271	4.5%	28,822	3,271	3,271
43	Material-recording and transport-clerk occupations, etc.	T8	120,871	50	0	0.0%	12,087	0	0
44	Other office and customer-service occupations	T1	20,557	34	615	3.0%	8,223	615	615
51	Service occupations	T7	156,322	29	16,813	10.8%	15,632	7,816	15,632
52	Retail sales occupations, etc.	T7	268,702	44	9,556	3.6%	26,870	9,556	9,556
53	Care occupations	T5	584,838	34	68,036	11.6%	116,968	58,484	68,036
54	Other security and protective service occupations	T7	44,666	25	3,548	7.9%	4,467	2,233	3,548
61	Agricultural and horticultural occupations	T8	42,193	21	3,116	7.4%	4,219	2,110	3,116
62	Forestry workers, fish	T8	4,896	24	350	7.2%	490	245	350

	farmers and fishers								
71	Building and civil-engineering occupations	T8	186,898	20	19,301	10.3%	18,690	9,345	18,690
72	Metal-trade and repair occupations	T8	148,306	16	0	0.0%	14,831	0	0
73	Precision, handicraft and craft-printing occupations	T8	9,299	39	108	1.2%	930	108	108
74	Electrical and electronics installation and repair occupations	T8	60,557	28	5,346	8.8%	6,056	3,028	5,346
75	Other craft and related occupations in wood and textiles, etc.	T8	12,955	16	13	0.1%	1,296	13	13
76	Food-processing craft occupations	T8	9,042	30	0	0.0%	904	0	0
81	Process and machine operators	T8	115,538	17	112	0.1%	11,554	112	112
82	Assemblers	T8	57,233	26	0	0.0%	5,723	0	0
83	Transport and machine-operator occupations	T9	161,206	17	2,908	1.8%	48,362	2,908	2,908
91	Cleaners	T8	105,278	11	6,179	5.9%	10,528	5,264	6,179
92	Agricultural, forestry and fishery labourers, etc.	T8	5,302	3	103	1.9%	530	103	103
93	Other occupations in construction, manufacturing and goods handling	T8	25,814	8	659	2.6%	2,581	659	659
94	Fast-food workers, kitchen and restaurant assistants, etc.	T7	105,688	6	5,396	5.1%	10,569	5,284	5,396
95	Market and street vendors	T7	280	55	32	11.5%	28	14	28
96	Refuse workers, newspaper deliverers and other service labourers	T8	49,833	22	2,552	5.1%	4,983	2,492	2,552
	Total (excl. unknown)		4,818,896		270,972		865,670	223,132	268,575

B.2 Check: 147 occupational groups (SSYK 3-digit). Columns: employees 2024 (SCB, K062, summed from SSYK 4-digit), 2035 shortfall (AF base scenario, K082), break-even (shortfall divided by employees), freed up in Mid, and remaining shortfall in Low and Mid. Type and percentage are the same as in B.1. See chapter 6.5.

SSYK	Occupational group	Type	Empl.	Shortfall	B-E	Freed M	Rem. L	Rem. M
011	Officers	T10	2,161	462	21.4%	216	354	246
021	Specialist officers	T10	4,803	836	17.4%	480	596	356
031	Soldiers, etc.	T10	7,010	574	8.2%	701	224	0
111	Politicians and senior officials	T4	2,334	185	7.9%	350	0	0
112	Chief executives, etc.	T4	22,132	262	1.2%	3,320	0	0
121	Finance and administrative managers	T4	20,698	380	1.8%	3,105	0	0
122	Human resource managers	T4	11,098	234	2.1%	1,665	0	0
123	Policy and planning managers	T4	12,059	909	7.5%	1,809	0	0
124	Information, communications and PR managers	T4	5,294	120	2.3%	794	0	0
125	Sales and marketing managers	T4	38,206	0	0.0%	5,731	0	0
129	Other administration and service managers	T4	29,286	1,046	3.6%	4,393	0	0
131	IT managers	T4	15,947	0	0.0%	2,392	0	0
132	Procurement, logistics and transport managers	T4	13,824	0	0.0%	2,074	0	0
133	Research and development managers	T4	7,716	0	0.0%	1,157	0	0
134	Managers in architecture and engineering activities	T4	15,085	0	0.0%	2,263	0	0
135	Property and facilities managers	T4	5,577	1,321	23.7%	837	763	484
136	Construction, civil engineering and mining operations managers	T4	20,536	1,913	9.3%	3,080	0	0
137	Manufacturing managers	T4	16,870	0	0.0%	2,530	0	0
138	Forestry and agriculture managers, etc.	T4	1,101	9	0.8%	165	0	0
141	Primary and secondary education and adult-education managers	T4	12,707	0	0.0%	1,906	0	0
142	Preschool managers	T4	4,083	0	0.0%	612	0	0
149	Other	T4	1,121	15	1.3%	168	0	0

	education managers							
151	Health-care managers	T4	13,835	2,219	16.0%	2,075	836	144
152	Social and pastoral-care managers	T4	5,751	697	12.1%	863	122	0
153	Elderly-care managers	T4	11,003	1,484	13.5%	1,650	384	0
154	Religious managers and leaders	T4	818	89	10.9%	123	7	0
159	Other public-service managers	T4	20,268	1,805	8.9%	3,040	0	0
161	Banking, finance and insurance managers	T2	5,851	0	0.0%	1,755	0	0
171	Hotel and conference managers	T4	1,836	245	13.3%	275	61	0
172	Restaurant and kitchen managers	T4	10,700	581	5.4%	1,605	0	0
173	Retail managers	T4	9,596	245	2.6%	1,439	0	0
174	Wellness, sport and recreation managers	T4	1,705	167	9.8%	256	0	0
179	Other service-industry managers	T4	7,933	169	2.1%	1,190	0	0
211	Physicists and chemists, etc.	T3	8,530	0	0.0%	1,280	0	0
212	Mathematicians, actuaries and statisticians	T3	2,764	30	1.1%	415	0	0
213	Biologists, pharmacologists and agricultural/forestry specialists, etc.	T3	8,587	450	5.2%	1,288	0	0
214	Engineering professionals	T3	125,052	0	0.0%	18,758	0	0
216	Architects and surveyors	T3	13,309	1,214	9.1%	1,996	0	0
217	Designers	T3	19,702	0	0.0%	2,955	0	0
218	Environmental and occupational health specialists	T3	10,840	665	6.1%	1,626	0	0
221	Physicians	T5	47,496	7,448	15.7%	9,499	2,698	0
222	Nurses	T5	111,672	17,325	15.5%	22,334	6,158	0
224	Psychologists and psychotherapists	T5	11,222	1,781	15.9%	2,244	659	0
225	Veterinarians	T5	3,067	252	8.2%	613	0	0
226	Dentists	T5	7,239	1,019	14.1%	1,448	295	0
227	Physiotherapists and occupational therapists, etc.	T5	22,084	3,542	16.0%	4,417	1,334	0
228	Other health-care specialists	T5	10,991	1,196	10.9%	2,198	97	0
231	University and higher-education teachers	T6	38,461	0	0.0%	5,769	0	0

232	Vocational teachers	T6	11,435	0	0.0%	1,715	0	0
233	Upper-secondary teachers	T6	28,591	0	0.0%	4,289	0	0
234	Primary teachers, leisure-time pedagogues and preschool teachers	T6	194,547	0	0.0%	29,182	0	0
235	Other teaching specialists	T6	36,329	0	0.0%	5,449	0	0
241	Auditors, financial analysts and fund managers, etc.	T2	60,996	2,549	4.2%	18,299	0	0
242	Organisational developers, policy analysts and HR specialists, etc.	T2	147,262	10,659	7.2%	44,179	0	0
243	Marketing and communications specialists, etc.	T2	50,942	300	0.6%	15,283	0	0
251	IT architects, software developers and test leaders, etc.	T3	180,127	0	0.0%	27,019	0	0
261	Lawyers	T3	28,659	1,379	4.8%	4,299	0	0
262	Museum curators and librarians, etc.	T3	11,641	926	8.0%	1,746	0	0
264	Authors, journalists and interpreters, etc.	T3	14,109	47	0.3%	2,116	0	0
265	Artists, musicians and actors, etc.	T3	11,859	1,271	10.7%	1,779	85	0
266	Social workers and counsellors, etc.	T3	52,567	6,567	12.5%	7,885	1,310	0
267	Clergy and deacons	T3	3,468	463	13.4%	520	116	0
311	Engineers and technicians	T3	119,416	412	0.3%	17,912	0	0
312	Construction and manufacturing supervisors, etc.	T3	28,045	943	3.4%	4,207	0	0
315	Pilots, ships' and aircraft officers, etc.	T3	5,931	148	2.5%	890	0	0
321	Biomedical scientists, dental technicians and laboratory engineers, etc.	T5	30,778	296	1.0%	6,156	0	0
323	Complementary-medicine therapists	T5	143	115	80.4%	29	101	86
324	Veterinary nurses, etc.	T5	2,973	70	2.4%	595	0	0
325	Dental hygienists	T5	3,597	550	15.3%	719	190	0
331	Bank clerks and	T2	62,845	2,294	3.7%	18,854	0	0

	accounting economists, etc.							
332	Insurance advisers, company sales agents and buyers, etc.	T2	146,681	0	0.0%	44,004	0	0
333	Brokers, etc.	T2	33,653	15,752	46.8%	10,096	9,021	5,656
334	Legal secretaries, executive secretaries and departmental secretaries, etc.	T2	19,071	1,099	5.8%	5,721	0	0
335	Tax and social-insurance officers, etc.	T2	48,158	4,665	9.7%	14,447	0	0
336	Police officers	T2	19,358	2,253	11.6%	5,807	0	0
341	Treatment assistants and pastors	T6	18,487	2,047	11.1%	2,773	198	0
342	Athletes and recreation leaders, etc.	T6	37,648	2,056	5.5%	5,647	0	0
343	Photographers, decorators and entertainment artists, etc.	T6	8,755	405	4.6%	1,313	0	0
344	Driving instructors, etc.	T6	7,482	0	0.0%	1,122	0	0
345	Head chefs and sous-chefs	T6	4,343	236	5.4%	651	0	0
351	Operations, support and network technicians, etc.	T3	48,532	415	0.9%	7,280	0	0
352	Image, sound and lighting technicians, etc.	T3	5,554	302	5.4%	833	0	0
411	Office assistants and secretaries	T1	166,625	13,849	8.3%	66,650	0	0
421	Croupiers and debt collectors	T1	1,767	139	7.9%	707	0	0
422	Travel agents, customer-service staff and receptionists, etc.	T1	70,288	3,132	4.5%	28,115	0	0
432	Warehouse staff and transport clerks, etc.	T8	120,871	0	0.0%	12,087	0	0
441	Library and filing clerks, etc.	T1	2,836	253	8.9%	1,134	0	0
442	Postal workers and mail sorters	T1	12,788	305	2.4%	5,115	0	0
443	Elected officials	T1	4,933	57	1.2%	1,973	0	0
511	Cabin crew, train conductors and guides, etc.	T7	8,635	385	4.5%	864	0	0
512	Cooks	T7	45,865	2,130	4.6%	4,586	0	0
513	Head waiters, waiters and bartenders	T7	37,436	2,147	5.7%	3,744	275	0

514	Beauty and body-care therapists	T7	14,877	2,659	17.9%	1,488	1,915	1,171
515	Cleaning supervisors and caretakers, etc.	T7	44,924	9,254	20.6%	4,492	7,008	4,762
516	Other personal service workers	T7	4,585	238	5.2%	458	9	0
522	Shop sales assistants	T7	245,038	8,711	3.6%	24,504	0	0
523	Cashiers, etc.	T7	15,397	578	3.8%	1,540	0	0
524	Street and telemarketing salespersons, etc.	T7	8,267	267	3.2%	827	0	0
531	Childcare workers and teaching assistants, etc.	T5	128,534	0	0.0%	25,707	0	0
532	Assistant nurses	T5	170,252	26,959	15.8%	34,050	9,934	0
533	Care assistants	T5	89,351	12,783	14.3%	17,870	3,848	0
534	Care workers and personal assistants, etc.	T5	185,598	26,611	14.3%	37,120	8,051	0
535	Dental assistants	T5	11,103	1,683	15.2%	2,221	573	0
541	Other security and protective service occupations	T7	44,666	3,548	7.9%	4,467	1,315	0
611	Market-oriented crop growers	T8	23,500	2,503	10.7%	2,350	1,328	153
612	Animal breeders and keepers	T8	13,557	613	4.5%	1,356	0	0
613	Mixed crop and animal producers	T8	5,136	0	0.0%	514	0	0
621	Forestry workers	T8	3,573	310	8.7%	357	131	0
622	Fish farmers and fishers	T8	1,323	40	3.0%	132	0	0
711	Carpenters, bricklayers and construction workers	T8	115,359	12,629	10.9%	11,536	6,861	1,093
712	Roofers, floor layers and plumbers, etc.	T8	43,535	4,982	11.4%	4,354	2,805	628
713	Painters and chimney sweeps, etc.	T8	28,004	1,690	6.0%	2,800	290	0
721	Founders, welders and sheet-metal workers, etc.	T8	26,228	0	0.0%	2,623	0	0
722	Blacksmiths and toolmakers, etc.	T8	56,390	0	0.0%	5,639	0	0
723	Vehicle mechanics and repairers, etc.	T8	65,688	0	0.0%	6,569	0	0
731	Precision instrument makers and craft workers, etc.	T8	4,051	108	2.7%	405	0	0
732	Prepress technicians,	T8	5,248	0	0.0%	525	0	0

	printers and bookbinders, etc.							
741	Electrical and industrial electricians, etc.	T8	51,517	4,759	9.2%	5,152	2,183	0
742	Electronics repairers and telecommunications electricians, etc.	T8	9,040	587	6.5%	904	135	0
752	Wood finishers and cabinetmakers, etc.	T8	10,708	13	0.1%	1,071	0	0
753	Tailors, upholsterers and leather workers, etc.	T8	2,247	0	0.0%	225	0	0
761	Butchers, bakers and food processors, etc.	T8	9,042	0	0.0%	904	0	0
811	Ore-processing occupations and well-drillers, etc.	T8	10,371	0	0.0%	1,037	0	0
812	Metal-processing plant operators	T8	17,785	0	0.0%	1,778	0	0
813	Chemical and pharmaceutical plant and machine operators	T8	6,176	0	0.0%	618	0	0
814	Rubber, plastics and paper plant and machine operators	T8	13,918	0	0.0%	1,392	0	0
815	Textile, laundry and leather machine operators, etc.	T8	5,719	112	2.0%	572	0	0
816	Food-processing plant operators	T8	16,802	0	0.0%	1,680	0	0
817	Wood and paper-products process operators	T8	15,327	0	0.0%	1,533	0	0
818	Other process and machine operators	T8	7,903	0	0.0%	790	0	0
819	Plant and process controllers	T8	21,537	0	0.0%	2,154	0	0
821	Assemblers	T8	57,233	0	0.0%	5,723	0	0
831	Train drivers and railway station staff	T9	6,217	244	3.9%	1,865	0	0
832	Car, motorcycle and bicycle drivers	T9	28,700	0	0.0%	8,610	0	0
833	Heavy-truck and bus drivers	T9	80,010	1,319	1.6%	24,003	0	0
834	Mobile plant operators	T9	44,577	1,343	3.0%	13,373	0	0
835	Deck hands, etc.	T9	1,702	2	0.1%	511	0	0
911	Domestic and commercial	T8	97,763	5,518	5.6%	9,776	630	0

	cleaners, etc.							
912	Launderers, window cleaners and other cleaning workers	T8	7,515	660	8.8%	752	284	0
921	Agricultural, forestry and fishery labourers, etc.	T8	5,302	103	1.9%	530	0	0
931	Construction and civil-engineering labourers	T8	7,309	659	9.0%	731	294	0
932	Hand packers and other manufacturing labourers	T8	9,040	0	0.0%	904	0	0
933	Dockers and freight handlers, etc.	T8	9,465	0	0.0%	946	0	0
941	Fast-food workers, kitchen and restaurant assistants, etc.	T7	105,688	5,396	5.1%	10,569	112	0
952	Market and street vendors	T7	280	32	11.4%	28	18	4
961	Refuse workers	T8	10,300	1,127	10.9%	1,030	612	97
962	Newspaper deliverers, caretakers and other service workers	T8	39,533	1,425	3.6%	3,953	0	0
	Total (excl. unknown)		4,818,896	270,972	5.6%	865,670	74,219	14,881

Appendix C. Justification by impact type

Five lines per type: what the percentage means, which groups are included, why the level was chosen (the author's reasoning), support and counter-evidence in the material with evidence level, and where the assumption is contestable and what would change the level. Quotations in single quotation marks are the author's own wording in the working material.

T1 Office support and customer service

What the percentage means. Share of the type's labour need in 2035, relative to the baseline (2024 employees), that disappears at unchanged volume: Low 30%, Mid 40%, High 50%. This is a gross reduction; volume compensation is shown separately (V is low according to the author, 0% at the centre). Linear path ≈ 2.7 / 3.6 / 4.5 percentage points per year. All figures are [Assumption].

Groups and main mechanism. The groups 41 Office assistants and secretaries (166,625 employees, exposure 89), 42 Customer service occupations (72,055; 76) and 44 Other office and customer-service occupations (20,557; 34). Together 259,237 employees and 17,735 of AF's shortfall. Main mechanism 1: casework, analysis and customer contact that can be automated.

Why this level (the author's reasoning). The author judges that routine office and customer work is what is automated first and most: ‘high automation potential after longer system learning curves’ (42), ‘very high degree of automation’ (44) and ‘probably a very low estimate’ (41). This is the highest level in the model, and all three groups already had the author's values of 30/40/50. Assumption, not measured.

Support and counter-evidence in the material. Support: Brynjolfsson, Li & Raymond (K128): +14% resolved cases per hour in customer service, +34% for new agents (level 3, controlled setting; the study does not address employment). Klarna stated in 2024 that its AI assistant performed work equivalent to 700 full-time employees, but began hiring people again in 2025 (K135, K136, level 1). Counter-evidence: exposure did not predict employment change 2023–24 (K069, ρ = −0.04, level 3); Dillon et al. (K127): time savings without increased output (level 3). Adoption: 7% of UK firms use agentic AI (K080, level 2); 35% of Swedish firms use some form of AI (K120, level 2). No source measures a 30–50% reduction in employment within an occupational group.

Contestability and what would change the level. The highest levels in the model (around 100,000 people in Mid) with no measured support for the magnitude. Exposure for group 44 is low (34) despite the highest level. Change the level if SCB's occupational register for SSYK 41–42 shows an annual decline relative to the baseline clearly below about 3.6 percentage points (Mid) for two years running, or if Swedish adoption of customer-service automation is measured and found small.

T2 Casework, finance and administration

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 20%, Mid 30%, High 40%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 1.8 / 2.7 / 3.6 percentage points per year. All figures [Assumption].

Groups and main mechanism. 33 Casework and finance, tertiary education or equivalent (329,766; exposure 73), 16 Managers in banking, finance and insurance (5,851; 70) and 24 Advanced-level competence in economics and administration (259,200; 92). Together 594,817 employees and 39,572 of AF's shortfall. Group 33 is mixed: company sales staff 91,526, accounting economists 30,194, bank clerks 24,513, buyers 23,447, other case officers 22,634 and police officers 19,358 (SCB, occupational register at 4-digit level). Main mechanism 1.

Why this level (the author's reasoning). The author sees casework and finance as ‘the most affected sector, prime for automation’ (33), heavily manual analysis in banking and finance (16), and judges that AI affects group 24 ‘even more’ than the author's level. The type value is the weighted average of the author's figures (17.8 / 27.8 / 37.8) rounded to 20/30/40. Assumption.

Support and counter-evidence in the material. Support: Baslandze et al. (K125): routine office roles declining, and large firms expected to reduce staff (level 2–3, executive survey). Block reports staff reduced from just over 10,000 to under 6,000 citing AI (K106, level 1). Counter-evidence: Almega (K023): finance employment +6% and output −2%; information and communication output +20.1% and employment +1.1% (descriptive). Swedish youth study: ratio of young/older −3.9% at exposed employers (K021, under review); no youth effect visible in Finland (K124). K022: the estimate is halved with education controls.

Contestability and what would change the level. Second-largest contribution (about 178,000 in Mid). Group 33 is mixed (police officers, sales staff, bank clerks) but is kept as one type per the author's decision; the heterogeneity is noted in the text. Almega (K023) shows increased employment in finance. Change the level if SCB shows bank clerks and accounting economists not declining at a pace of about 2.7 percentage points per year (Mid).

T3 Experts (analysis, technology, IT, law)

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 10%, Mid 15%, High 20%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.9 / 1.4 / 1.8 percentage points per year. All figures [Assumption].

Groups and main mechanism. 21 Science and engineering (188,784; exposure 89), 25 IT (180,127; 98), 26 Law, culture and social work (122,303; 68), 31 Engineering, tertiary education or equivalent (153,392; 50) and 35 IT, sound and light (54,086; 74). Together 698,692 employees and 15,232 of AF's shortfall (AF: no shortfall for IT architects, software developers and test leaders). Group 26 includes, among others, social workers (27,020), where documentation support (mechanism 2) is the most concrete evidence, and translators (2,675). Main mechanism 1.

Why this level (the author's reasoning). The author judges that AI gives large tool gains in calculation, analysis, law and IT, but that people are needed ‘in the balance’ (25). At the same time the author sees IT as the sector that could shrink considerably, while many believe it will grow to serve AI; the investigation therefore only shows the figures, without arguing for either. The level sits below types 1 and 2 because the author sees AI as complementary for experts. The type value is the rounded average of the author's figures (11.9 / 16.9 / 21.9). Assumption. (The author's own demand-growth figure for group 25, +20%, is not used from v12 onward.)

Support and counter-evidence in the material. Support: K022: employment for 22–25-year-olds in the most-exposed occupations sits 19% below the comparison group via reduced new hiring (level 3, descriptive, US). Machine translation (K130): one percentage point more use is associated with 0.7 percentage points lower employment growth for translators (level 3). World Bank (K129): job postings in occupations AI can replace −12% (level 3). Counter-evidence: K019: AI-exposed Swedish workplaces hired more through 2022 (level 3, before generative AI); Dillon et al. (K127): no increased output despite time savings; Denmark: null effects on pay and hours two years after ChatGPT (K066). Documentation support for physicians: −9.5% time on chart notes (K151) and −0.36 h/day (K152) in controlled studies (level 3).

Contestability and what would change the level. Group 25 has the highest exposure (98) but the lowest level in the type; a critic may ask why the exposure measure does not drive the level. K022's findings concern young people and weaken with education controls. Change the level if SCB's occupational register shows declining employment among software developers (about 1.4 percentage points per year in Mid) or if K021 is published with stronger results.

T4 Managers and leaders

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 10%, Mid 15%, High 30%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.9 / 1.4 / 2.7 percentage points per year. All figures [Assumption].

Groups and main mechanism. 11 Politicians, chief executives and senior officials (24,466; exposure 65), 12 Managers in finance, HR, marketing and administration (116,641; 79), 13 Managers in IT, logistics, R&D, construction and manufacturing (96,656; 67), 14 Managers in education (17,911; 65), 15 Managers in health care (51,675; 68) and 17 Managers in other service industries (31,770; 48). Together 339,119 employees and 14,096 of AF's shortfall. Main mechanism 1: monitoring, planning and decision support.

Why this level (the author's reasoning). The author sees AI as support for monitoring, planning and decisions (12: ‘monitoring, planning and decision support’), with the largest effect for IT managers (13) and health-care managers (15). Group 11 is kept in the type at the author's decision: new ways of working increase capacity for politics, CEOs and senior officials too, so fewer people can take on greater responsibility and the need for labour falls. The type value is the rounded average (8.9 / 15.9 / 27.7). High 30% is driven by group 13 (40%), 15 (30%) and 12 (25%). Group 11 gets 15% in Mid, about 3,200 more people than the author's original 2%.

Support and counter-evidence in the material. Nothing in the material measures effects on managerial occupations, and nothing measures politicians or chief executives. Indirect support: exposure is high (48–79), and analysis and decision support are exactly what AI is strongest at (chapter 3.2). Counter-evidence: exposure did not predict employment change (K069); K019, K021 and K022 do not concern managers. The type rests entirely on assumption.

Contestability and what would change the level. The weakest basis of all types, and the range is wide (Low 10, High 30). Group 11 is the most contestable part: a critic may ask why politics and leadership need fewer people, and no study shows this. Change the level if studies of managerial occupations or of management structures become available.

T5 Care and health care

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 10%, Mid 20%, High 25%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.9 / 1.8 / 2.3 percentage points per year. All figures [Assumption].

Groups and main mechanism. 22 Advanced-level health-care competence (213,771; exposure 47), 32 Health care and laboratory, tertiary education or equivalent (37,491; 47) and 53 Care occupations (584,838; 34). Together 836,100 employees and 101,631 of AF's shortfall (37.5% of the entire shortfall). Main mechanism 2: data collection, documentation and analysis, with elements of planning.

Why this level (the author's reasoning). The author judges that documentation and administration make up a large part of care and health-care work and that AI can take over much of it, as well as giving ‘more optimal planning’ (53). The author describes physicians and nurses as a ‘very manual sector that is greatly affected’ (22). The type value is the rounded average (11.2 / 17.7 / 24.4) to 10/20/25, with the author retaining Low 10%. (The author's own assumptions about demand growth absent AI, +15% and +10%, are not used from v12 onward.)

Support and counter-evidence in the material. Support: controlled studies of documentation support for physicians: −9.5% time on chart notes with one of two tools (K151) and −0.36 h/day (K152) (level 3). Sensor alarms in senior housing gave slower functional decline (K153, level 3), and a French early-detection system shows high accuracy (K154). Time spent on documentation: in a Finnish survey, physicians, nurses and social workers spend on average 3 hours 14 minutes per day on documentation (K118, self-reported). Adoption: trials in Helsingborg (20 case officers per unit, K156) and Kalmar (project plan, K157); in Västra Nyland in Finland about 800 users estimate 29 minutes less documentation per day (K155, level 2). Vendor claim: Tandem Health on Eslöv, 59% shorter documentation time (K158, level 1). Counter-evidence: Denmark: null effects (K066); one of two tools in the UCLA study gave no reliable effect (K151); DAIOE exposure is low (34–47).

Contestability and what would change the level. Decides the Low scenario: 10% sits below care's break-even (11.6% for group 53 and 15.2% for group 22), so Low does not cover the full shortfall. Own calculation, not a source: if documentation takes about 3 hours per day and AI support reduces it by 10–50%, 18–90 minutes per day is freed up. The effect of analysis and early detection (chapter 3.2) cannot be converted into staff numbers with today's basis. The type is 19% of what is freed up in Mid and 37.5% of the shortfall. Tested in chapter 6.6; the author has chosen to retain 10/20/25%. Change the level if Swedish time studies for assistant nurses and nurses, or studies of care needs after adoption, become available.

T6 Education, culture and social work

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 10%, Mid 15%, High 20%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.9 / 1.4 / 1.8 percentage points per year. All figures [Assumption].

Groups and main mechanism. 23 Advanced-level teaching competence (309,363; exposure 72), including primary-school teachers 114,915, preschool teachers 62,036 and upper-secondary teachers 28,591, and 34 Culture, wellness and social work, tertiary education or equivalent (76,715; 45), including treatment assistants

17,406, recreation leaders 17,076 and sports coaches 15,286. Together 386,078 employees and 4,743 of AF's shortfall. Main mechanism 1 (analysis, planning) with elements of 2.

Why this level (the author's reasoning). The author judges that education is affected ‘strongly through analysis and management’ and access to AI-driven knowledge (23), and that administration and documentation disappear in social work and wellness (34). The type value is the rounded average (8.9 / 13.3 / 17.9) to 10/15/20. Assumption.

Support and counter-evidence in the material. Support: IFN (K020): university and higher-education teachers among the most-exposed occupations (exposure, not effect). Documentation support is measured for physicians (K151, K152), not for teachers or treatment assistants. Counter-evidence: no study in the material measures an effect on teachers; K019, K021 and K022 concern other occupations or ages; demand in schools is driven by pupil numbers, and birth rates are falling (about 97,500 born in 2025). The type rests on assumption.

Contestability and what would change the level. Group 34 is mixed (treatment assistants, sports coaches) and fits the mechanism poorly; demand for teachers is driven by pupil numbers. Change the level if Swedish studies of teachers or preschool teachers become available.

T7 Service, retail and security

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 5%, Mid 10%, High 15%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.5 / 0.9 / 1.4 percentage points per year. All figures [Assumption].

Groups and main mechanism. 51 Service occupations (156,322; exposure 29), 52 Retail sales occupations (268,702; 44), 54 Security and protective services (44,666; 25), 94 Fast food, kitchen and restaurant (105,688; 7) and 95 Market and street vendors (280; 55). Together 575,658 employees and 35,345 of AF's shortfall. Main mechanism 2: data collection, documentation and analysis around otherwise manual, customer-facing work.

Why this level (the author's reasoning). The author judges that in service-near occupations it is mainly the administration that disappears (51: ‘the administration disappears, which is a significant share’; 52: ‘everyday admin’), not the customer contact itself. The type value is the rounded average (6.8 / 10.7 / 14.5) to 5/10/15. Assumption.

Support and counter-evidence in the material. Nothing in the material measures effects in retail, service, restaurants or security. K022's ADP sample under-represents retail and restaurants specifically. Exposure is low (7–55). Counter-evidence: exposure did not predict employment change (K069). The level rests on an assumed share of documentation and administration that is not measured.

Contestability and what would change the level. 575,658 employees and about 58,000 people in Mid, without measurement. Change the level if measurements of self-service and administration automation in retail become available.

T8 Crafts, manufacturing, warehousing and cleaning

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 5%, Mid 10%, High 15%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.5 / 0.9 / 1.4 percentage points per year. All figures [Assumption].

Groups and main mechanism. Crafts and construction: 71 Building and civil engineering (186,898; exposure 20), 72 Metal and repairers (148,306; 16), 74 Electrical and electronics installation (60,557; 28), 61 Agriculture and horticulture (42,193; 21), 76 Food-processing crafts (9,042; 31), 73 Precision and graphic crafts (9,299; 39), 75 Wood and textiles (12,955; 16), 62 Forestry and fishing (4,896; 24). Manufacturing, warehousing and cleaning: 43 Material recording (120,871; 50), 81 Process and machine operators (115,538; 17), 82 Assemblers (57,233; 26), 91 Cleaning (105,278; 11), 92 Agricultural labourers (5,302; 3), 93 Other construction, manufacturing and goods-handling occupations (25,814; 9), 96 Recycling, etc. (49,833; 22). Together 954,015 employees and 37,838 of AF's shortfall (71 Construction: 19,300). Main mechanism 2 (documentation and analysis) for crafts, and 3 (automation) for manufacturing, warehousing and cleaning.

Why this level (the author's reasoning). The author judges that in crafts and construction it is mainly the daily administration that disappears (‘the daily admin disappears’) while the physical work remains, and that warehousing and materials handling are affected because ‘admin, documentation and system interaction become automated’ (43), cleaning because ‘cleaning robots increase’ (91), and machine operators and assemblers through daily admin (81, 82). The two types had the same values (5/10/15) and were merged with the author's approval. Assumption.

Support and counter-evidence in the material. Nothing in the material measures effects in crafts, construction, agriculture, forestry, warehousing or cleaning. IFN (K020): among the least-exposed occupations are construction labourers. Exposure is low (3–50). Historical comparison, not AI: productivity growth has reduced employment in its own industry but not in the economy as a whole (K132). The level rests on an assumed share of documentation and administration and an assumed pace of cleaning and warehouse automation, both without a source.

Contestability and what would change the level. A broad type (15 groups, 954,015 employees, about 95,000 people in Mid) without an AI-specific source; a critic may ask why 5/10/15 and not 0. It is possible to show that the conclusion does not hinge on this type by setting it to 0–5% as a sensitivity check. Change the level if measurements of the administration share in construction and crafts, warehouse automation, or cleaning robots in Sweden become available.

T9 Vehicle drivers

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 20%, Mid 30%, High 40%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 1.8 / 2.7 / 3.6 percentage points per year. All figures [Assumption].

Groups and main mechanism. 83 Transport and machine-operator occupations (161,206 employees; exposure 17), including truck drivers 58,463 and taxi drivers 12,809. AF shortfall 2,908. Main mechanism 3: autonomous vehicles.

Why this level (the author's reasoning). The author judges that autonomous vehicles give ‘great potential’ (83). The level is unchanged from the author's figures (20/30/40) and is the only occupational group where mechanism 3 carries the level alone. Assumption about technology, regulation and pace.

Support and counter-evidence in the material. Regulatory position (context, not adoption): according to the Swedish Transport Agency (K117), commercial traffic with fully self-driving heavy trucks without a driver is not permitted in Sweden; trials require a driver in the vehicle or remote, at low speeds. The Transport Agency has a government mandate to follow and negotiate regulatory developments (published 2026-05-21), a v1 framework instruction in 2026 and a regulatory-model review (RISE/VTI) exist, and the EU is developing type approval. No driverless transport is operational in Sweden. The exposure measure (DAIOE) does not measure physical automation (exposure 17). No data on adoption or effect on drivers exists in the material.

Contestability and what would change the level. The level of 20–40% (about 32,000–64,000 people) rests on assumptions about technology, regulation and pace; the regulatory situation suggests slow rollout in Sweden, but development is faster in the US (K117). Change the level if Swedish regulation or deployment diverges from the assumption, or if adoption is measured.

T10 Defence

What the percentage means. Share of the type's labour need in 2035 that disappears at unchanged volume: Low 5%, Mid 10%, High 20%. Gross reduction; volume compensation shown separately (V low, 0% at centre). Linear path ≈ 0.5 / 0.9 / 1.8 percentage points per year. All figures [Assumption].

Groups and main mechanism. 01 Officers (2,161), 02 Specialist officers (4,803) and 03 Soldiers, etc. (7,010); exposure data missing. Together 13,974 employees and 1,872 of AF's shortfall. Main mechanism 3.

Why this level (the author's reasoning). The author judges that technological developments in Ukraine show the need for front-line soldiers falling, that command structures shrink with technology, and that logistics become automated; the effect could become quite large. Defence's own growth is a separate figure that should not be linked to the AI-efficiency effect, and the net is likely to be an increase in need. The type value is the rounded average of the author's figures (4.2 / 10.7 / 21.5) to 5/10/20. Assumption.

Support and counter-evidence in the material. No support in the material: no source measures the effect of technology on defence staffing, and the Ukraine observation is not documented. Defence staffing is governed by political decisions on expansion.

Contestability and what would change the level. The effect on the result is small (about 1,400 people in Mid). Net: the AI-efficiency effect is reported here and defence's own growth separately (with the author's growth assumption of +20 to +30%, the net becomes about +12% in Mid: 15,723 against 13,974 today, own calculation). The author judges that the AI effect could be larger than 5/10/20. Change the level if defence's own plans or studies become available.

Appendix D. Source register

This appendix lists the sources the investigation cites by K-number. The sources are held in the investigation's source library. Level-1 material (companies' and vendors' own statements, and commercial analyses) is presented as perspective, not as evidence (chapter 3.3).

D.1 Sources K001–K118

ID	Source	Used in
K001	AI Commission, Roadmap for Sweden, SOU 2025:12	4.2, 8.1, 11.2
K002	Adaptations to the AI Act, SOU 2025:101	4.2, 8.6
K004	Government of Sweden, Sweden's AI strategy (February 2026)	4.2, 11.1
K005	Privacy-enhancing technology in public administration, SOU 2026:44	4.2, 8.1
K009	The Wage Effects of Generative AI (SSRN 5842084)	4.10
K012	Frank et al., AI-exposed jobs deteriorated before ChatGPT (arXiv 2601.02554)	4.4
K019	Engberg et al., Artificial Intelligence, Hiring and Employment (Ratio WP 380)	4.3
K020	IFN, Exposure to generative AI in Sweden (2024)	Appendix C
K021	Lodefalk, Löthman, Koch & Engberg, Same Storm, Different Boats (version 2026-09-30)	4.3, Appendix C
K022	Brynjolfsson, Chandar & Chen, Canaries in the Coal Mine (Aug 2026)	4.4, Appendix C
K023	Almega, Three years with AI (2026-05-07)	4.3, Appendix C
K026	Hershbein & Kahn, Do Recessions Accelerate Routine-Biased Technological Change? (NBER w22762)	7.4
K027	Stanford HAI, The 2025 AI Index Report	8.3, 9.2
K028	Epoch AI, LLM inference prices have fallen rapidly but unequally across tasks	8.3
K039	Epoch AI, Where Autonomy Works (2026-02-10)	8.4
K040	Electrek, Musk admits no Optimus robots are doing 'useful work' (2026-01-28)	8.4
K041	Tech Times, China Ships 90% of Global Units (2026-06-18)	8.4
K043	MIT Technology Review, The human work behind humanoid robots (2026-02-23)	8.4, 10
K051	Intellectia, The $700 Billion AI Infrastructure Boom (2026)	9.3
K052	Bloomberg, AI Demand Begins to Justify Massive Cost of Data-Center Buildout (2026-06-25)	9.3, 10
K053–K055	KPMG, VATCalc, Bloomberg Law on taxation of AI (May 2026)	9.4
K056	Riksdag, interpellation 2025/26:414, National plan for new data centres	9.6
K062	SCB, Occupational register with occupational statistics 2024	2, 5, 6, Appendix B
K066	Humlum & Vestergaard, Still Waters, Rapid Currents (Denmark)	4.4, Appendix C
K068	METR, Time Horizon 1.1 (2026-01-29)	4.7, 8.2
K069	Gupta & Kumar, Agentic AI and Occupational Displacement (arXiv 2604.00186)	4.7, 5.4
K080	UK DSIT, Artificial Intelligence Adoption Research (Jan 2026)	4.7, 12.3
K081	Arbetsförmedlingen, Labour shortage and labour from abroad (AF Analys 2026:04)	2, 5, 6, 11, Appendix B
K082	Arbetsförmedlingen, Appendix: table basis for AF Analys 2026:04	2, 5, 6, 11, Appendix B
K083	Nordström Skans & Sokolow Romin, Structural transformation and AI, Tillväxtanalys 2026:17	4.3, 11.5
K084	Hellsten, Khanna, Lodefalk & Yakymovych, The Effects of AI on Jobs: Evidence from an AI Subsidy Program (IZA DP 18267)	4.3
K085	Riksbank, Monetary Policy Report March 2026, pp. 31–	4.2, 4.3, 8.1

	34	
K096	Autor et al., New Frontiers: The Origins and Content of New Work (NBER w30389)	7.3
K097	Yotzov, Barrero et al., Firm Data on AI (NBER w34836)	4.5
K106	Block, Inc., Q4 2025 Shareholder Letter (8-K, Exhibit 99.1)	4.6, Appendix C
K113	SCB, Sweden's population 2025 (statistical news 2026-02-24)	2.3
K117	Swedish Transport Agency, Automated road transport (regulatory position)	8.5, Appendix C
K118	Ministry of Social Affairs and Health (Finland), review of documentation in social welfare and health care	6.6, Appendix C

D.2 Sources K119–K177

Column 2 gives the address as recorded in the source register (domain, URL fragment or library note), not a full citation.

ID	Source	Address
K119	SCB, Sweden's future population 2026–2070 (statistical news 2026-04-16)	scb.se
K120	SCB, Use of AI in enterprises 2025 (statistical news 2025-12-11)	scb.se
K121	SKR, Welfare's skills supply 2023–2033 (2024)	skr.se
K122	GBD 2021 Fertility and Forecasting Collaborators, The Lancet 2024	doi.org/10.1016/S0140-6736(24)00550-6
K123	Caixin, article on China's 2025 population statistics (2026-01-19), reporting China's statistics bureau	caixinglobal.com
K124	Kauhanen & Rouvinen, ETLA Working Papers 135 (2026-01-27)	etla.fi
K125	Baslandze et al., AI, Productivity, and the Workforce: Evidence from Corporate Executives (NBER w34984)	nber.org/papers/w34984
K126	UK Department for Business and Trade, Microsoft 365 Copilot evaluation (Aug 2025)	gov.uk
K127	Dillon, Jaffe, Immorlica & Stanton, Shifting Work Patterns with Generative AI (NBER w33795)	nber.org/papers/w33795
K128	Brynjolfsson, Li & Raymond, Generative AI at Work, Quarterly Journal of Economics 2025 (NBER w31161)	nber.org/papers/w31161
K129	Liu, Wang & Yu, World Bank Policy Research Working Paper 11263	documents.worldbank.org
K130	Frey & Llanos-Paredes, machine translation and translators' employment, CEPR VoxEU 2025	cepr.org/voxeu
K131	Nordhaus, Baumol's Diseases: A Macroeconomic Perspective (NBER w12218, 2006)	nber.org/papers/w12218
K132	Autor & Salomons, Is Automation Labor-Displacing? Brookings Papers on Economic Activity, spring 2018	brookings.edu (BPEA)
K133	David, The Dynamo and the Computer, American Economic Review 80(2), 1990	jstor.org
K134	Brynjolfsson, Rock & Syverson, The Productivity J-Curve, American Economic Journal: Macroeconomics 13(1), 2021	doi.org/10.1257/mac.20180386
K135	Klarna, press release on the AI assistant (2024-02-27)	prnewswire.com
K136	Klarna's CEO to Bloomberg on quality and rehiring (May 2025), reported by PYMNTS	pymnts.com
K137	Swedish Pensions Agency, target age and forecast (2026)	pensionsmyndigheten.se
K138	Regulation (EU) 2026/1744 (digital omnibus on AI)	eur-lex.europa.eu
K139	Regulation (EU) 2023/1230 on machinery	eur-lex.europa.eu
K140	Bain & Company, Technology Report 2026	SharePoint evidence library (held)
K141	Google, announcement on token volume, Q3 2025	blog.google
K142	Alphabet, Q4 2025 earnings release (8-K, February 2026), including 2026 investment plan	abc.xyz / sec.gov
K143	Nvidia, Q4 and full-year fiscal 2026 results (8-K, February 2026)	nvidianews.nvidia.com / sec.gov
K144	Data Center Watch, reports on local opposition to data centres (2025)	datacenterwatch.org
K145	William Fry, on CRU's decision on connecting large power customers in Ireland (December 2025)	williamfry.com
K146	Future of Life Institute, Statement on Superintelligence (2025-10-22)	superintelligence-statement.org
K147	Future of Life Institute, Pause Giant AI Experiments: An Open Letter (2023)	futureoflife.org
K148	SCB, Municipal tax rates 2026	scb.se
K149	Swedish Tax Agency, Employer contributions 2026	skatteverket.se
K150	SCB, Average monthly pay by sector 2025 (wage structure statistics, whole economy)	scb.se
K151	Lukac et al., randomised study of AI documentation at UCLA, NEJM AI 2025	ai.nejm.org
K152	Afshar et al., AI documentation and documentation time, NEJM AI 2025	ai.nejm.org
K153	Rantz et al., Randomized Trial of Intelligent Sensor	pubmed.ncbi.nlm.nih.gov

	System for Early Illness Alerts in Senior Housing, JAMDA 2017	
K154	Presage Care, pragmatic study of early detection among older home-care recipients, JMIR 2024	jmir.org
K155	Västra Nyland wellbeing region, AI-assisted documentation, press release	sttinfo.fi
K156	City of Helsingborg, data protection impact assessment (DPIA), Blink of an AI (2024-09-03)	media.helsingborg.se
K157	Kalmar municipality, project plan, AI speech-to-text	kalmar.se
K158	Tandem Health, customer case, Eslöv municipality	tandemhealth.ai
K159	Evident, AI Index 2025 (banks)	evidentinsights.com
K160	SKR's standing committee on workforce supply, Kraftsamling för välfärdens kompetensförsörjning – action plan with combined support (long version, 2024)	Held in the library (saved by the author)
K162	LO, Shorter working hours – facts, research and conditions (LO's working-time review, final report 2025), ISBN 978-91-566-3752-0	lo.se
K163	Alphabet, Q4 2025 earnings call, CEO remarks (2026-02-04)	blog.google / abc.xyz
K164	Alphabet, Q3 2025 earnings call (2025-10-29)	abc.xyz; reported by, among others, The Motley Fool
K165	ABN Amro, press release ahead of Capital Markets Day (2025-11-25)	abnamro.com
K166	Nordea, stock-exchange release on restructuring costs (2026-03-17)	nordea.com
K167	Standard Chartered, announcement 19 May 2026 (RNS); Bloomberg 19 May and Alliance News 20 May 2026	investegate.co.uk; bloomberg.com; morningstar.co.uk
K168	JPMorgan Chase, investor day 19 May 2025, reported by Business Insider and eFinancialCareers	businessinsider.com; efinancialcareers.com
K169	Swedbank, 2026 savings programme, reported by Dagens PS (citing SVT and ERR)	dagensps.se
K170	Morgan Stanley, staff reduction March 2026, reported by Invezz (Reuters, Wall Street Journal)	invezz.com
K171	Bloomberg Intelligence, survey of IT managers at 93 banks (January 2025), reported by, among others, Entrepreneur and Finextra	entrepreneur.com; finextra.com
K172	Ingeniøren, Danish banks lay off thousands of workers: AI revolution or just spin? (11 June 2026)	ing.dk
K173	Government of India, decision on the IndiaAI Mission (March 2024), budget 10,371.92 crore rupees	narendramodi.in; pib.gov.in
K174	Riksdag, State Budget 2026 – the Framework Decision (bet. 2025/26:FiU1)	riksdagen.se
K175	Riksbank, annual average exchange rates 2025 (exchange rates for tax returns)	riksbank.se
K176	IBISWorld, Global Car & Automobile Manufacturing (April 2025)	ibisworld.com
K177	Swedish Tax Agency, Tax deduction for monthly pay 2026, table 32 (SKVFS 2025:20)	skatteverket.se

Appendix E. Glossary

Agentic AI. AI that itself plans and carries out multi-step tasks, within given rules.

Assumption, Source, Reference. Labelling of values in the calculation by origin (chapter 3.4).

Baseline. Number of employees in 2024 by occupational group; the starting point for the calculation.

Break-even. The reduction in labour need, as a percentage of the baseline, required to cover the shortfall.

Shortfall (deficit). AF's calculated difference between labour demand in 2035 and the number employed that would then exist if nothing else changes, in number of people (chapter 2.1).

DAIOE. Index of how exposed occupations are to AI, linked to AI benchmark results.

Substitution. A process is carried out by AI without a human performing it operationally.

Exposure. How large a share of an occupation's tasks AI can, in principle, carry out; says nothing about actual use.

Augmentation. AI makes a person faster or better at a task they still perform.

Freed-up labour capacity. The part of the labour need that disappears when work can be done with less effort; expressed in number of employees.

Main mechanism. The way in which AI is judged to affect an occupation the most (1–3).

Remaining shortfall. The part of an occupational group's shortfall not covered by what is freed up within the group itself.

Low, Mid, High. Three scenarios for how large the effect becomes by 2035: cautious assumption, intermediate, and rapid diffusion.

Level 1/2/3. Classification of evidence: supply/capacity, adoption, outcome.

Impact type. A group of occupations with the same assumed effect (T1–T10).

SSYK. The Swedish Standard Classification of Occupations (SSYK 2012).

Token. The unit in which AI models count text; roughly a fraction of a word.

Volume compensation (V). The share of the reduction offset by increased demand when prices fall.

Surplus. Freed-up labour capacity beyond what is needed to cover the shortfall, expressed in number of employees. Not a number of unemployed people (chapters 6.2 and 6.11).

Appendix F. Visionen – the author's conceptual background material (2025–2026)

During 2025 and early 2026, Per Högberg produced a series of documents on how operations in the municipal sector could be developed with the support of agentic AI. The documents are conceptual: they describe architecture, ways of working and intended benefits, not implemented systems or measured effects. They are presented here to show where the author's picture of what is technically possible comes from (chapter 0.3–0.4). No values in the calculation are drawn from them.

Table F.1 Visionen's documents

Document	Content in brief
Presentation of Visionen (August 2025)	Why welfare needs to be restructured as fewer people are left to do more, and that digital tools and AI are aids, not goals.
Visionen – elderly care, in depth (September 2025)	A platform bringing together planning of interventions and staff, knowledge support, registered and measured values, and assessment support, with support for benefit recipients, staff and relatives.
Visionen – administration, in depth (dated 2025-09-09)	A single digital entry point to the municipality's services for citizens, staff and elected officials, drawing information from the municipality's existing systems: casework, democracy and participation, transparency and decision support.
Visionen – the basic platform, in depth (September 2025)	The common foundation: information model and data platform, integration with municipalities' operational systems, data governance, law, ethics and security, and a national architecture for AI.
Visionen – school, in depth (dated 2025-11-07)	A platform for scheduling, learning materials, assessment and decision support for teachers and school leadership, grounded in the curriculum and in the perspective of pupils and guardians.
Administration – concept sketch, public version (January 2026)	Design principles for an AI-based service portal for citizens using only the municipality's public information, with language and accessibility as a basic function and clear limits on what AI may do; AI shall never make decisions.

Dates as given in the documents or, where no date appears in the text, according to the files' properties.

Common to the documents is the starting point that welfare needs to be restructured quickly where there are not enough people to staff it, and that this should happen through increased quality, security and quality of life. The documents describe themselves as a handrail, not a finished manual.

Link to the investigation: Visionen gives concrete examples, in municipal operations, of the three steps in chapter 3.2 – collection, analysis and action. The investigation picks up where Visionen leaves off, with the question of how large the effect becomes on the need for labour.