Foreword

In recent months, there has been considerable discussion about AI and how it will affect society. In this memorandum, we attempt to quantify the impact that today's available AI tools could have on Norwegian society if implemented. Specifically, we look at the potential to streamline the time spent on solving current work tasks. Technology in general, and artificial intelligence in particular, has the potential to reshape the way we work and live, and we cannot yet predict how such efficiency gains will be realised. Nearly 100 years ago, John Maynard Keynes predicted that technological growth would result in increased leisure time, but we have not yet seen this. Therefore, in the memorandum, we do not try to say how, but how much.

Many have tried before us, but what's unique about our approach is that we integrate established international research methodology with Norwegian data to provide estimates that are more relevant to Norwegian professions, industries, and counties. Although the estimates are subject to great uncertainty, they offer valuable insights for anyone trying to plan for an uncertain future, or shape it.

Menon Economics is a research-based analysis and consultancy firm at the intersection of business economics, national economy, and industrial policy. We offer analysis and consultancy services to businesses, organisations, and the public sector. Our primary focus is on empirical analyses of economic policy, and our staff possess economic expertise at a high scientific level.

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# Summary

Our main findings indicate that approximately 70 percent of the Norwegian workforce could reduce their working hours by 10 percent as a result of efficiencies through the use of AI tools. For nearly half of the workforce, this gain could be as high as 20 percent, which, in theory, could reduce the average workweek by a full day. We also observe a clear correlation between higher wage groups and greater efficiency potential, with particularly strong effects within professional groups such as engineers, mathematicians, and programmers.

Within the business sector, results indicate that service-oriented industries such as legal and accounting services, financing, and administration possess a potential for efficiency improvements equivalent to one-third of current tasks. Overall, 90 percent of industries exhibit an efficiency ratio above 10 percent through the use of AI, demonstrating the broad application of technology across various industry groups with diverse skills and requirements.

It's not only the private sector that can reap efficiency gains by implementing AI into their tasks. By fully utilising AI as the technology stands today, the public sector can streamline tasks which would annually equate to 155,000 full-time equivalents in sectors such as health, education, and public administration.

Geographically, the potential for efficiency is highest in Oslo, Viken, and Trøndelag, but the differences between the counties are minimal, suggesting a relatively even occupational distribution at the national level. When it comes to industries, service sectors such as legal and financial services have significantly higher potential for efficiency, while occupations with a high degree of human interaction have fewer opportunities.

With our method, we have the capability to undertake a more detailed approach to geographic effects. Our analysis indicates that the potential for efficiency in Norway's municipalities varies, with the highest potential for efficiency in the municipalities surrounding Oslo at around 20 percent, and between 15 and 20 percent in other municipalities where the public sector dominates. It is the larger municipalities with many employed, especially those with service-oriented professions such as Bærum, Oslo, and Asker, where we see the greatest potential for efficiency gains.

We have further calculated the annual value of all the tasks that AI could potentially automate in the Norwegian economy. We find that full utilisation of AI in the workforce as estimated in this memo corresponds to an annual value creation in Norway of between 500 and 600 billion Norwegian kroner. This amounts to around 17 percent of Mainland Norway's GDP for 2022. This figure only represents the efficiency gains from current tasks and does not include gains from new AI-driven innovation.

Finally, we look at AI's possible effect on unemployment. AI is expected to influence the Norwegian labour market, but overall we consider it unlikely that it will lead to significant unemployment. Historically, technological revolutions have created new jobs and increased demand such that unemployment has been stable or has even fallen. This suggests that AI might instead increase productivity and contribute to economic growth. Nevertheless, it is relevant to point out that pockets of unemployment could arise in certain regions or industries as a result of implementing AI. Here, we highlight that politicians should take an active role in addressing such challenges through further education, retraining, and the broader industrial policy.

# Introduction

Since the launch of ChatGPT in November 2022, the business sector, in particular, has become increasingly aware of the immense potential of large language models (LLMs) and other forms of generative artificial intelligence (AI). Merely months after its launch, OpenAI demonstrated significant advancements with a new version: GPT-4. The technology is continuously evolving, but the available versions already exhibit capabilities that will, in the long term, be of great importance for many parts of our society, including the job market. Previous research conducted by OpenAI itself has highlighted substantial gains from the use of ChatGPT and similar tools in the American job market. In this analysis note, we explore, with an advanced development of OpenAI's methodology, the consequences of AI tools on the Norwegian job market.

Large language models like GPT-4 are the result of advanced machine learning, where billions of parameters are finely tuned through training on vast amounts of text. These models are designed to ingest text and speculate on a new set of text based on a mathematical similarity to the text that was fed in. The methodology has demonstrated a high degree of flexibility and potential. The models prove to be capable of a variety of more or less expected tasks, including translation, text processing, idea sparring, complex problem-solving, and code development.

Although language models have their weaknesses, especially when it comes to generating accurate and fact-based information, the latest version, GPT-4, represents a significant improvement over the previous version, GPT-3. GPT-4 has the ability to program video games from scratch with minimal human input, pass the American bar exam with high marks, and speaks Hebrew better than its predecessor spoke English. These advanced capabilities highlight the wide spectrum of applications where language models may come to play a critical role in the future.

This analysis note aims to provide a deeper understanding of how artificial intelligence (AI) and language models can impact the Norwegian labour market in a variety of ways, and offers a framework for policymakers, business leaders, and academics to navigate this complex landscape. In that context, it is important to understand that the impact of AI on the workforce is not binary, but rather falls along a spectrum of possible outcomes.

At one end of this spectrum, we find full automation of existing professions as the most dramatic form of change. Here, AI technologies have the potential to significantly replace human labour. This is particularly relevant in occupations where a large proportion of the tasks can be performed by AI, without the need for compensatory human effort. Such a upheaval has already been seen in cases such as when the online newspaper Gizmodo furloughed its Spanish section in favour of AI-driven translations. We have also witnessed this historically with the automation of professions like telephone operators, which do not exist today. The consequences for employees educated within the professions affected by this type of full automation can range from internal relocation, jobs in other professions or unemployment.

On the completely other end of the spectrum, we find occupations where AI has little or no noticeable effect. This is particularly the case in professions dominated by physical labour or where human interaction plays a central role. Such professions include healthcare personnel such as nurses and therapists, where the emotional connection and patient care are key. Similarly, this applies to common trade professions like carpenters, plumbers, or bricklayers who will likely be minimally affected by language models.

For the vast majority of professions, however, the potential for efficiency gains will fall between these extremes. In this middle position on the influence spectrum, artificial intelligence does not necessarily lead to the replacement of labour but rather to an enhancement of productivity and efficiency in existing professions. This can manifest itself in various ways, from enabling workers to complete the same tasks with fewer resources, to performing new tasks that previously required a higher level of professional competence. This latter phenomenon, often referred to as the "augmentation effect", may for instance occur when a nurse is able to carry out diagnostic tasks previously reserved for doctors, without the need for doctors diminishing.

Given this broad spectrum of possible outcomes, it is important to understand the economic, social, and political implications of AI in the labour market. Just as the labour movement ensured improved working conditions in the wake of the industrial revolution, the AI revolution offers a unique opportunity to reassess and perhaps restructure the working week further.

### Assessment of AI's Impact on the Labour Market in the Literature

The large range in potential for efficiency across professions makes it difficult to assess the overall impact of AI-driven efficiency on both the labour market and the economy. However, some research has been conducted on the topic, and below we briefly review some of the key contributions to the field.

After six months of access to advanced language models, the global unemployment rate has remained stable, as confirmed by a recent OECD study. The study finds no significant decrease in the demand for human labour. A likely reason is that we are still in an early phase of technological adoption, where it takes time to identify the most effective areas of application. Additionally, the study indicates that companies may be reluctant to lay off and dismiss employees, preferring instead to let the workforce reduce naturally through retirement and voluntary resignations. This observed stability in the labour market aligns well with Everett Rogers' theory of "Diffusion of Innovations", which explains that new technology is adopted in stages, with a small group of innovators leading the way. The rest of the market often waits to see their success before following suit. Consequently, we can expect the most significant changes to become apparent as the technology matures and becomes more widely accepted.

At the same time, an increasing number of studies indicate that large language models lead to positive gains in the labour market. For instance, a study by Erik Brynjolfsson et al. demonstrated that access to an AI-based conversational assistant increased productivity by an average of 14 percent among customer service workers. Novices and low-qualified workers saw an improvement of 35 percent in productivity, which supports the argument that AI can act as a catalyst for increased efficiency, particularly among less experienced workers. A study by Fabrizio Dell’Acqua and others, carried out with the Boston Consulting Group, corroborates this by showing that consultants completed 12 percent more work tasks, 25 percent faster and with 40 percent better quality compared with a control group within a set timeframe. Again, it was the lowest qualified workers who experienced the most significant improvement in productivity and quality at 43 percent. The study also highlighted the importance of understanding the capabilities of AI. In tasks where AI has limited abilities, consultants had a 19 percent lower probability of performing tasks correctly with AI assistance compared with those without help.

Another study by Shakked Noy and Whitney Zhang found that assistant chatbots like ChatGPT could significantly increase productivity in writing tasks, reducing time spent by 40 percent and improving output quality by 18 percent. This demonstrates that even in complex, creative tasks, AI can have a markedly positive effect.

At the end of this analysis, we provide a brief assessment of the effects of automation on the national economy and labour market in Norway. Our objective is to offer a comprehensive and nuanced understanding of how AI can shape the Norwegian labour market, focusing on the economic, social, and political challenges, and opportunities, that lie ahead.

# Results

In this chapter, we will explore and discuss the quantitative findings from our analysis of the potential for efficiency improvements in the Norwegian labour market. We find, among other things, that the average Norwegian can make their work 17 percent more efficient through the use of available AI tools. However, there is a wide range, with some professions having the potential to reduce their working hours by up to 60 percent. Nevertheless, this applies to only a few, and we find that the majority of the workforce has an efficiency potential of under 20 percent. We also observe that the potential for efficiency gains is higher for well-paid professions.

When we look at which sectors have the greatest potential for efficiency gains, these are dominated by service-providing industries. The most exposed sectors (accounting services) have potential efficiency gains of just over 40 percent, while the least exposed (for example food service and cleaning) have potential gains of under 10 percent. We also calculate the efficiency potential for counties – here, we find significantly less variation between the most exposed (Oslo and Viken) and the least exposed (Innlandet, and Møre og Romsdal). Finally, in the analysis, we calculate the total value of the efficiency potential. This is estimated at a full 500 billion Norwegian kroner annually, which corresponds to 14 percent of Mainland Norway's GDP in 2022.

We aim to provide a detailed overview of the potential for automation and efficiency through artificial intelligence for various professions and salary groups. The figures we present for the efficiency potential in percentage are an estimate of the total time saved, based on how many work tasks can be streamlined through the use of AI.

Our study follows the method described in the GPTs are GPTs study, with some adaptations. The study employs a combination of human expertise and GPT-4 classifications to assess AI's impact on each individual work task. Unlike OpenAI's study, our method takes a more conservative approach to the classification of work tasks to provide a more realistic and robust picture of the technology's potential influence, and we have made some adjustments to the rubric used for classification.

## The average Norwegian can save 17 percent of their working hours with AI.

The impact of efficiency gains on the Norwegian labour market is determined by several factors. For instance, the outcome of the AI revolution will depend on how many are affected, and which occupational groups they belong to. If there are few employees in the professions with the most potential for efficiency gains, the impact at the national level will be minimal. Similarly, the productivity and wage distribution in the affected professions will influence the size of the societal benefits and consequences. To form a complete picture of AI's effect on the workforce, we therefore use employment figures per occupational level to ascertain the impact per employed person, and illustrate the result below.

Figure 1: Proportion of Norwegian employment with a given potential for efficiency improvement. Proportion and cumulative proportion. Source: SSB and Menon Economics.



The figure illustrates the overarching potential for efficiency gains in the Norwegian workforce. As we can see from the figure, 30 percent of the workforce has an efficiency gain potential of between 0 and 10 percent. This means that approximately 70 percent of the employed population could expect an efficiency gain of at least 10 percent, while nearly 40 percent may envisage a gain of 20 percent. Additionally, about 1 percent, equivalent to around 25,000 individuals, could potentially achieve an efficiency gain of 40 percent or higher.

This suggests that a large portion of the workforce is facing potential automation and efficiency effects. We have also highlighted the average potential for efficiency for a typical Norwegian worker, which stands at 17 percent (calculated as the average of efficiency potential per profession weighted against the number of employed individuals). This means that if the economic gain allows it, the average Norwegian could reduce their work week by nearly one full workday.

## Up to 50 percent efficiency potential in the most exposed occupations

We observe that there are clear differences in potential for efficiency across professions; this is due to the abilities of language models being better suited to some tasks than others. The wage statistics suggest that there is a bias towards tasks that are commonly found in higher-paid professions. We are therefore examining the professions directly, to see which groups are most affected.

Figure 2: Occupational groups with the highest potential for efficiency gains (potential time savings in percentage). Source: SSB and Menon Economics



Figure 2 shows the 15 occupations with the highest potential for efficiency gains, where the maximum time saving is over 50 percent. We also note that a 60 percent efficiency potential is the maximum achievable time saving in our analysis. This reflects the fact that work tasks involving text processing, posed to large language models, are particularly vulnerable. Furthermore, AI tools are especially adept at coding tasks, which explains why professions such as engineers, mathematicians, statisticians, and programmers are among the most affected. Another important observation is that the AI tools' ability to efficiently plan and structure data impacts occupations that include many management- and organisation-related tasks.

Although telecommunications and radio and television broadcasting may at first glance appear to be unexpected additions, they make sense upon closer examination. Telecommunications are dominated by technical engineering positions, marketers, and salespeople, while radio and television broadcasting have a high concentration of journalists – a professional group with significant potential for efficiency improvement. This sector also includes case handlers, engineers, and translators, all of whom can benefit from the capacities of AI tools.

At the bottom of the list for potential efficiency gains, we find occupations such as bricklayers, cleaners, plumbers, and roofers. These types of jobs require a high degree of manual skill and adaptability in varying and unpredictable work environments. As we can see at the top end of the potential for efficiency, AI excels in predictable and text-intensive tasks, but when it comes to physical work requiring continual adaptation, AI is less applicable.

## Highest efficiency potential in higher-paid groups

Historically, technology has primarily favoured the higher educated workforce. This has occurred because much of the technology has automated manual tasks, while increasing the demand for highly skilled labour. This has contributed to the wage gap between low and high educated labourers widening in most Western economies. Relative to historical periods of automation, LLMs and other modern AI differ in their ability to perform and automate non-manual and non-physical tasks. All else being equal, this suggests that the potential for efficiency gains will be highest among analytical professions, which are often occupied by highly educated labour, whilst manual jobs, particularly those involving a significant degree of human contact, will not be affected to the same extent.

To test this, we have calculated the average efficiency potential for different salary levels. This is shown in the figure below.

Figure 3: Efficiency potential divided into groups by salary. Source: Menon Economics, Statistics Norway



In the figure, we see a clear upward trend. Although there is a significant variation in the efficiency potential within each wage group, we observe a general tendency for higher salaries to correlate with greater efficiency potential. The average efficiency potential is around 10 percent for wage groups below 600,000 NOK, but this figure doubles for groups earning above 600,000 NOK. If we repeat the calculation for average time savings in the previous subsection, but also take into consideration the salary in each profession, the average national efficiency potential increases to 18.5 percent.

The impact of skewed wage structures can manifest in various ways. Agrawal et al. highlight an augmentation effect, rather than automation in many professions. This implies that AI tools can facilitate the tasks of lower-skilled workers. An illustrative example is the driving industry, where there were 200,000 professional taxi and limousine drivers in the USA in 2018. Today, more than 10 times as many drive for Uber alone, thanks to readily available GPS technology, which has led to a decline in wage levels. Another example is in the health and care sector, where healthcare personnel are increasingly able to take on diagnostic tasks from doctors, resulting in higher salaries and better career opportunities.

## Service industries have the highest potential for efficiency gains.

Further, we aggregate the occupations up to the industry level. Figure 4 below illustrates the potential for efficiency gains in percentage terms for the nine most and five least exposed industries. The lower axis shows the potential for efficiency gains in percentage for the industry, where the proportion is represented by the blue bar chart. The upper axis shows the number of employees in each of the industries, where the quantity is represented by the orange dots.

Figure 4. Weighted exposure potential and total number of employed for various industries. Source: SSB and Menon Economics



From the figure, we see that many industries have the potential to make a quarter of their working hours more efficient. It is principally the service industries that have a high potential for efficiency gains. The most exposed industries also share characteristics, such as being text- and information-intensive. These industries also include tasks that involve large volumes of data, repetitive information processing, or customer interactions, areas where artificial intelligence has proven to be valuable. Furthermore, we see that the top industries often require higher education and are generally better paid than those with lower exposure. An example is "Legal and accounting services", which stands out with a weighted efficiency potential of over 35 percent. Artificial intelligence has proven to be highly effective at reading, processing, and summarizing large quantities of literature and figures, which can be beneficial for lawyers to quickly extract important information from legal decisions and laws, a task that would take longer for humans.

"The 'financial services' sector also has many tasks that can be made more efficient, as the work in this sector is characterised by extensive data analysis and decision support – areas where artificial intelligence has proven to have strong capabilities. The potential for efficiency improvements in this industry is just below 30 percent. We also see services related to information technology and information services on the list. This is a sector that has generally been early to embrace digitalisation, and artificial intelligence will likely only enhance this effect."

The remaining industries gradually decrease from 25 percent down to the lowest at 6 percent, which is "Services related to property management". Unlike the most exposed industries, the least exposed industries have work tasks that require direct human interaction, physical labour, and human skills, tasks that artificial intelligence currently cannot perform. These industries also have a greater number of unique and less repetitive tasks, and often encounter more unpredictable events that must be managed by humans.  
  
Immediately, the percentage efficiency potential is not the most crucial factor for achieving gains through the implementation of artificial intelligence; it depends on the total gain potential which also relies on the number of employees whose tasks can be optimised. The upper axis represents the number of employees in the different industries, and for instance, "Public administration and defence" have over 140,000 employees with over 25 percent efficiency potential. This equates to 35,000 employees in the industry, a figure that corresponds to all the employees in Ålesund. Hence, the implementation of artificial intelligence in this sector could have a significant overall impact on their production.

## Evenly distributed potential for efficiency across various counties

We have also examined the geographical distribution of the potential for efficiency at the county level. In the figure below, we present the weighted potential for efficiency for all Norwegian counties.

Figure 5. Efficiency potential in Norway's eleven counties. Source: Statistics Norway and Menon Economics



From the figure, we can see that Oslo is most exposed to efficiency gains driven by artificial intelligence. Our model indicates a potential for efficiency improvements of 20 percent of the workforce, corresponding to 100,000 employed individuals. This is closely followed by Viken and Vestfold and Telemark, with efficiency potential at respectively 17 and 15.8 percent, which equates to 89,000 employed in Viken and 30,000 in Vestfold and Telemark. The counties with the lowest degree of exposure are Nordland, Trøndelag, and Møre og Romsdal, with an exposure rate around 15 percent. This corresponds to 20-30 thousand employed individuals.

There is not a significant difference in the potential for efficiency gains from Oslo, with the highest at 20 percent, to Nordland, with the lowest at 15 percent. This may indicate that the occupational distribution in the counties is quite similar, at least with regard to the distribution of potential efficiency gains in percentage terms. Naturally, counties with many employees within the most exposed industries will also have a greater potential for efficiency gains at the county level. To investigate this, we have used statistics from SSB on the distribution of industries among employees in different counties. When examining the industry group professional, scientific, and technical services – which includes professions such as legal and accounting services and administrative consulting, we see even after adjusting for population size that Oslo and Viken have 55 percent of all employees in this industry. The three least exposed counties only represent 6 percent of employees in the same industry category. At the same time, Oslo and Viken represent a smaller, but significant portion of the industries with the lowest potential for efficiency gains, with 33 percent of all employees in the 10 industries with the lowest potential for efficiency gains. This contributes to a smaller difference in the potential for efficiency gains between the counties.

Overall, all counties can reap an efficiency potential of over 15 percent by industries utilising artificial intelligence in their tasks. However, it is most likely that the technology will first be implemented in larger counties where the industries have more employees, since there are often start-up costs and economies of scale associated with implementing artificial intelligence in the workflow.

Based on our methodology, we can zoom in even further to identify where the potential for efficiency is greatest. The figure below illustrates the potential for efficiency across all Norwegian municipalities. The degree of exposure is represented by a colour ranging from white to red, with white being less exposed and red being more exposed. The exposure potential varies from under 14 percent to over 20 percent among the municipalities.

Figure 6. Map showing the efficiency potential for Norwegian municipalities. Source: SSB, Geonorge and Menon Economics.



The diagram further illustrates that the municipalities surrounding the capital Oslo are the most exposed. There are also some municipalities in Northern Norway that stand out due to a high proportion of employees linked to the public sector, where many occupations have considerable potential for efficiency improvement.

We will take a closer look at this in Figure 7, where we show the potential for efficiency at the municipal level for the ten most exposed municipalities.

Figure 7. The ten Norwegian municipalities with the greatest potential for efficiency. Source: SSB and Menon Economics



The figure illustrates a comparison of the potential for efficiency gains through the use of AI, measured against the number of thousand employed in each municipality. In the figure, we can observe that the ten municipalities have a fairly similar potential for efficiency gains, from 20.5 percent in Bærum to 18.8 percent in Trondheim.

In the figure, we do not see a clear correlation between the potential for efficiency and the number of employed individuals. For instance, we observe Nesodden with only 9,300 employees, displaying a potential for efficiency at the level of Bærum and Oslo. It must be noted that the smaller municipalities in the figure are all in proximity to Oslo, and share many of the same occupational characteristics as Oslo. These are municipalities with a high proportion of employees in service-oriented professions, where previous results indicated that the potential for efficiency is high. Because of this similarity, it can be expected that the municipalities will adopt the same approaches to the use of AI in work tasks.

However, it is easier to see a correlation between the number of employed individuals and the degree of efficiency when we look at all the municipalities. This is illustrated in the figure below.

Figure 8. Efficiency potential versus number of employees in the municipalities. Source: SSB and Menon Economics



In the figure, we can observe that there is much more variation in the number of employed where the potential for efficiency is high. Where the potential for efficiency is low, we only find municipalities with a low number of employed. This is an important part of the picture, as the total efficiency gain will be even greater for the larger municipalities with many employees and high potential for efficiency. The municipalities with the lowest potential for efficiency have a number of employed from 500 to 5,000, and thus the total gain to be made is not as significant. In the figure below, we will examine the municipalities with the lowest potential for efficiency in more detail.

Figure 9. Efficiency potential in percentage for the Norwegian municipalities with the least potential. Source: SSB and Menon Economics



As shown in Figure 8, the municipalities with the least potential for streamlining also have the lowest number of employed persons. Frøya has the highest and Røst the lowest number of employees, with respectively 2,700 and 173 employed. We observe that the efficiency rate ranges from the highest in Hattfjelldal at 13 percent, down to the lowest in Røst municipality, at 11.5 percent. The lowest potential for streamlining is approximately half of the streamlining potential of the highest.

Generally, we observe a gradual decrease in efficiency potential from 20 percent down to 11.5 percent in the Norwegian municipalities. The variation in the number of employed across municipalities is reduced with the decline in efficiency potential. Although there is nearly a halving in efficiency potential from Bærum to Røst, there will be opportunities to reap benefits by implementing AI in all of Norway's municipalities and counties. This will be elaborated upon in the upcoming chapter on the value of efficiency potential.

## In the public sector, there is a particularly large potential for efficiency gains within case processing.

The figure below illustrates the potential for increased efficiency in the public sector by using AI. The axis in the figure represents the number of full-time equivalent positions AI could potentially cover if the potential is fully exploited. The values are obtained by multiplying the efficiency potential with the number of employees in the profession. This immediately means that professions with the highest values do not necessarily have to have the highest efficiency potential in percentage terms, as we have seen before.

Figure 10. Top 10 efficiency potential in the public sector. Source: SSB and Menon Economics



The figure immediately indicates that there is significant potential for AI to represent tens of thousands of man-years in the public sector. At the top of the list, we find the occupation "Higher Case Workers in Public and Private Enterprise", where AI can streamline a workload that corresponds to 22,000 man-years. This represents one-third of the workforce in 2022. Similar to many of the occupations with considerable potential for efficiency improvements earlier in the report, the responsibilities of a case worker consist of investigating and responding to applications, documents, and other inquiries, tasks where AI has proven to be exceptionally efficient.

We also find teaching professions high on the list, with efficiency potential between 5 and 15,000 full-time equivalents, and an efficiency potential of between 15 and 20 percent. These are occupations consisting of many tasks where AI is not yet effective due to the necessity of human interaction and skills in dealing with children and the elderly. However, there are also many work tasks involving coordination and communication, both internally within the organisation and externally towards users, where AI can yield significant benefits by increasing efficiency for these tasks.

Subsequently, several caring professions follow, where AI can cover between six and nine thousand full-time equivalents. Caring professions also require a lot of personal contact with people and patients, but the care-oriented tasks coincide with a lot of coordination and communication work where AI can provide support. Examples of this may include medical record writing, patient follow-up, and information processing. Further down the list, we find occupations such as office workers, with 5,400 saved full-time equivalents, where AI's ability to perform administrative tasks, organise documents and assist with communication can yield benefits in the form of efficiency improvements.

In the figure below, we also look at the counties with the greatest potential for efficiency gains, solely with regard to the industries we define as the public sector.

Figure 11. County-distributed potential for efficiency improvements in the public sector. Source: Statistics Norway and Menon Economics



From the figure, we can draw many of the same conclusions as when we analysed the counties in general. First, we see that all counties have a somewhat higher potential for efficiency when we look solely at the business groups in the public sector, compared to all Norwegian industries. We also see that the differences between the municipalities are now smaller. This is not surprising since we are only looking at the public sector, where the distribution of employed people will be more similar across the different counties. Again, Oslo is most exposed to AI-driven efficiency improvements. In contrast to the previous figure, we now see that the counties of Troms and Finnmark, as well as Nordland, are higher on the list, while Trøndelag, Rogaland, Vestfold, and Telemark have dropped down. This may indicate that the professions previously mentioned are more concentrated among those employed in the public sector.

Our model suggests that there is potential for significant gains associated with AI in the public sector across all counties. If all occupational groups in the public sector implemented AI to the extent the potential indicates, this could contribute to a time reduction equivalent to 155,000 full-time equivalents annually. This figure represents almost 18 percent of all those employed in the selected industries and may be part of the solution to the challenges of ageing, labour shortages, and healthcare personnel in Norway.

## Despite considerable uncertainty, AI is not expected to lead to significant unemployment in Norway.

Given the significant potential identified above, there is reason to believe that AI will have a considerable impact on the Norwegian labour market in the coming years. In this context, it is interesting to discuss to what extent the implementation of AI is expected to lead to significant unemployment, or whether the effect of AI will primarily be realised in the form of higher production and thus a higher level of welfare.

Norway also faces a challenge with a shortage of labour, as documented in numerous periodic analyses from, among others, NAV and NHO. This shortage of labour suggests that, in isolation, the impact of AI on unemployment could be limited, as individuals who may lose their jobs will be employed by other companies in need of labour, or will find new work tasks within the same organisation.

The same conclusion is reached when examining historical episodes of major technological revolutions. Historically, technological advancements have rarely led to large-scale unemployment. Going back to the Industrial Revolution in the 1800s, when mechanisation and automation began to transform manufacturing processes, there were concerns that craftsmen and textile workers would lose their jobs. However, this revolution also led to the creation of new jobs in manufacturing, machinery maintenance and infrastructure, and even within the management and planning of the new industry. The same effect was seen in the automation that took place in both agriculture and industry in the second half of the 20th century. This did not result in high unemployment, but instead created a range of new professions primarily within the service sector. This is supported by the study by Fabrizio Dell’Acqua et al., where the results showed that the least qualified workers saw the greatest improvement in productivity and quality by implementing AI in their work process. Increased productivity among the previously less qualified makes them more profitable to employ for businesses. In this case, this can result in lower unemployment and higher productivity.

It is, however, worth mentioning that several claim that modern language models and AI technologies differ significantly from previous revolutions. This is justified by the technology being considered substantially more revolutionary than other technologies, with capabilities much closer to human ones than, for example, automation in industry.

It is important to note that although certain professions may experience automation of parts of or all work tasks, it does not necessarily mean that people will remain unemployed. For some, this will mean increased productivity, which gives businesses the opportunity to increase their production and growth with the same workforce. Others will be able to be retrained to perform other tasks that require human effort, and some will even find new job opportunities through retraining and further education.

Based on the above analyses and observations, there is reason to believe that the introduction of artificial intelligence and language models into the Norwegian labour market will not lead to significant unemployment. Instead, we assess that these technologies will more likely stimulate higher productivity and efficiency in various sectors. This could potentially lead to increased growth and competitiveness for the business community and thus help to maintain the demand for labour. At the same time, this is not a predetermined conclusion: how the business community and politicians choose to handle the implementation and regulation of AI technologies over the coming years may be decisive.

Finally, it is important to stress that although there is not a significant risk of systemic unemployment, there is a risk that certain regions or industries may experience pockets of unemployment as a result of AI. Therefore, it is crucial that policymakers take an active role in developing strategies to handle such situations. This may include measures for retraining, support for business development in affected areas, and investment in infrastructure and technology to promote economic diversity and resilience. Having a comprehensive approach to these challenges is essential to ensure that benefits and risks associated with AI development are evenly distributed and managed.

## The potential for efficiency savings is worth up to 570 billion Norwegian kroner annually.

As previously discussed, this streamlining could result in either increased production for the same amount of effort, increased leisure time, or increased unemployment. In the first two cases, the streamlining entails socioeconomic benefits. We can estimate the size of this benefit based on figures from Menon's accounting database, the county-distributed national accounts, and the calculated potential for streamlining at the county level. In total, we estimate this at over 570 billion kroner annually, which corresponds to about 17 percent of Mainland Norway's GDP. It is important to be precise in the interpretation of this figure. It represents the value of the combined work tasks that we estimate AI can automate in the Norwegian economy. There is, of course, considerable uncertainty associated with this figure.

Distributed across counties, we find the value of the AI-driven efficiency, as shown in the figure below:

Figure 12. The value of efficiency potential from AI, based on work tasks in 2022. Source: SSB, Menon Economics



In the figure above, we see that AI in 2022 could have contributed to a value creation in Oslo of NOK 134 billion annually. Furthermore, we observe that Viken and Vestland have the potential to generate NOK 114 billion and NOK 63 billion annually, respectively. The northernmost counties have the lowest potential for value creation with AI, with a potential value creation of approximately NOK 25 billion. These are only estimates, but they can provide insight into the potential gains AI could offer in monetary terms.

These estimates come with the caveat that AI only streamlines the tasks currently being performed, and do not take into account the additional benefits AI could offer by enabling work we are currently unable to do at all, which could provide even larger gains. This, in isolation, drives up the value of AI. On the other hand, it is at least equally important to emphasise that there is little reason to believe that AI will actually be implemented for all the tasks where it is potentially possible. Implementing AI can be both challenging and cost-driving, which means that the actual impact on the Norwegian economy will be somewhat less. Furthermore, implementation will not happen overnight, and the actual impact will be spread over several years.

# Methodology

The purpose is to assess the efficiency potential of various occupations as a result of generative AI, where we define the efficiency potential as the degree of time-saving in a profession. To arrive at this figure, we have broken down occupations into their individual work tasks and used AI to classify each work task according to its exposure to AI tools. We divide the work tasks into four categories: minimal effect (ME), good effect (GE), effect with additional tools (EE), and effect with visual capabilities (ES). The latter two categories mean that the work task can be efficiently improved if the language model has an additional ecosystem built around it, or the ability to see images or videos. We then use these categories to quantify the efficiency potential based on the number of work tasks that can be improved in each profession, this is the descriptive factor further in the analysis. In this chapter, we provide a thorough and technical explanation of our approach to data and modelling.

## A combination of American and Norwegian data

In our analysis, we utilise an advancement of the methodology described in "GPTs are GPTs" by OpenAI. Similar to OpenAI, we make use of the O\*NET database, which contains a list of over 923 occupations and corresponding job tasks. Each occupational group in the database has on average 20 different job tasks described.

The O\*NET database is an American database and does not correspond to the occupational data issued by Statistics Norway. We therefore use a cross-reference dataset from the US Bureau of Labor Statistics to convert the various occupational codes to ISCO, which harmonises with the Norwegian occupational data.

Further, supplementary statistics for each professional group are sourced from the Central Bureau of Statistics (CBS) for further analysis.

08536: Gender and industry distribution (88 groups) among employed persons (15-74 years). 4th quarter (Q) 2008 – 2022: This table describes the employment of residents in Norway at a detailed level. The data have been used to examine the potential for efficiency improvements at the industry and county levels.

Employed persons aged 15-74, by county of work. Number and percentage. 4th quarter: This table describes the employment for residents in Norway at a detailed and regional level.

09391: Main figures county-distributed national accounts, by region, statistical variable and year: This table displays the county-distributed national accounts.

Special order from SSB: This table contains even more finely meshed data on the employed in Norway than the usual tables SSB provides. Here we find the number of employed within a specific occupation for all industries. The table also includes an ISCO-08 code, which is used to link the table to our data on the potential for efficiency in percentage.

## Minor adjustments to the model from GPTs are GPTs.

The model we use to assess the potential for streamlining in various professions is based on the categorisation of tasks using a language model, more specifically the GPT-4 engine. Each task is categorised into one of four possible categories (ME, GE, EE, and ES) using a detailed instruction sheet (See Appendix 1), which clarifies the conditions for each category.

To enhance the accuracy of our analysis, the results of GPT-4's categorisation are compared with a smaller sample of manually categorised tasks, which aids in identifying significant contradictions between human and GPT-4 choices. Additionally, results are evaluated continuously throughout the analysis process to uncover any inconsistencies. For instance, certain particularly challenging occupational groups, among others "Dispatchers, Except Police, Fire, and Ambulance" and "Telemarketers", are examined for each categorisation to assess accuracy. These two occupations contain tasks that involve verbal communication, where GPT-4 tends to suggest optimisation by continuously generating scripts. It was precisely this feature that was tested by Brynjolfsson et al., concluding with good effect for inexperienced employees, but little to no benefit for experienced ones.

Two metric indicators, and , are then used to quantify a composite score per occupation. is calculated as a weighted proportion of tasks categorised as "Good effect," where core tasks are weighted double according to the O\*NET database. is an extension of and also includes "effect with extra tools" and "effect with visual abilities," but only with 50 percent weighting. The unweighted formulas are, respectively,

The final result is a dataset of 923 occupational rows, each with a score calculated using the "+" or "-" indicators. Ultimately, we calculate the potential for efficiency by multiplying the "+" score by 0.6. This is done to obtain a number that can be interpreted as a direct time saving, because the categories are defined as a time reduction between 50 and 100 percent. 60 percent has been chosen as a conservative estimate.

### We link occupational data with industry data to analyse the variation.

Further, the dataset is linked to employment figures for the Norwegian labour market, thereby providing important indications of how large language models may come to affect the workforce in Norway. We have used employment tables from Statistics Norway (SSB) and linked the potential for efficiency gains of occupations with the occupational compositions within various Norwegian industry codes. To determine the potential for efficiency gains in the different industries, we multiplied the efficiency potential of occupations by the number of employees per occupation and summed the result for each industry. The classification of the industry standard and industry codes is based on SN2007 from Statistics Norway (SSB).

We have further used these data to perform analyses at the county level by linking the data with relevant tables on industry distribution from Statistics Norway. An analysis focusing on the public sector has also been conducted, by defining the public sector as the industries "Public administration and defence; compulsory social security", "Education", and "Human health and social work activities". These industries mainly consist of employees in the public sector, although there may also be employees from private sectors, for example, private healthcare services. The possible inclusion of private services also means that the total number of employees is somewhat higher than for the public sector alone.

In the public sector, we often find the same professions as we do in the business sector in general, but the distribution of the number of employees in the professions is often different. To prevent us from merely repeating the results we find at the occupational level, we have chosen to multiply the efficiency potential by the number of employees in each occupation to estimate the number of "full-time equivalents" AI can cover. This means that it will not only be the efficiency potential in percentage that will have an impact, but also the number of people employed in the profession.

An important caveat is that these calculations are merely estimates, as the link between efficiency potential in percentage terms for sectors translated into geographical effects can be imprecise. For instance, a county may have a different internal job distribution within a sector than the distribution at a national level, and thus our grouping could erroneously weight the tasks as being either too much or too little in terms of efficiency compared to what is actual for that county's sector group.

### We employ a more conservative categorisation.

A key difference between our method and that employed by OpenAI's article is related to the categorisation of each individual work task. Unlike OpenAI, we conduct the analysis five times for each work task, which yields slightly different results each time. The variations in the answers can be attributed to several factors. One of them is the built-in stochastic properties of the language model, which means that identical inputs will not always generate exactly the same output. Furthermore, there have also been minor adjustments to the instructions throughout the study. As the categorisation has taken place over a six-month period, some of the variations come as a natural consequence of continuous development and updating of GPT-4.

Our conservative strategy entails that we systematically choose the most pessimistic of the five answers that the model generates. If one of five answers is "Minimal effect," this becomes the preferred response. In this way, we believe to present a more realistic and robust picture of how advanced language models like GPT-4 can impact the efficiency in various professions.

A comparison between our conservative method and the one used by OpenAI is visualized in Figure 1. It shows the distribution of -score (the distribution will be the same for the potential for efficiency, but with values between 0 and 0.6). From this figure, we can discern a certain optimistic bias, where several professions have all their work tasks affected. We interpret that GPT-4 tends to overestimate its own ability to automate or streamline tasks and therefore believe the conservative distribution we use is more realistic.

Figure 13: Efficiency potential in the Norwegian labour market using two methodological approaches. Source: Menon Economics.



# Attachment: Heading

Below is the heading that has been used as instruction for the language model. We have used OpenAI's method as a starting point, and therefore the categories have slightly different names. In the rubric, E0, E1, E2, and E3 correspond to our categories ME, GE, EE, and ES.

# E Exposure Taxonomy

Consider the most powerful OpenAI large language model (LLM). This model is capable of completing numerous tasks.

that can be formulated as having text input and text output where the context for the input can be captured in 2000 words. The model also cannot produce up-to-date facts (those from less than 1 year ago) unless they are included in the input.

Assume you are an employee with an average level of expertise in your role attempting to carry out the given task. You have access to the LLM as well as any other existing software or computer hardware tools mentioned in the task. You also have access to any commonly available technical tools accessible via a laptop (e.g., a microphone, speakers, etc.). You do not have access to any other physical tools or materials.

Please classify the given task according to the taxonomy below. ## E0 – No exposure

Label tasks E0 if direct access to the LLM through an interface such as ChatGPT or the OpenAI playground cannot reduce the time it takes to complete this task with equivalent quality by half or more.

If a task necessitates a high level of human interaction (for instance, face-to-face demonstrations), then it should be categorised as E0.

Label as E0 or E2 if the task requires real-time verbal correspondence or audio communication via radio or telephone, even if an LLM could assist by writing scripts.

Highly specialised and repetitive tasks are probably carried out often by the worker, thus the usefulness of the LLM may be confined to the initial learning stage of the job and should be categorised as E0. Designate as E0 if an LLM contributes solely to the reduction of time the first instance the task is performed.

## E1 – Direct Exposure

Label tasks E1 if direct access to the LLM via an interface such as ChatGPT or the OpenAI playground alone can halve the time needed to execute the task while maintaining equivalent quality. This encompasses tasks reducible to: - Composing and transforming text and code as per complex directives, - Applying revisions to prevailing text or code in accordance with specifications, - Authoring code that facilitates the completion of a manually performed task, - Translating text between languages, - Summarising medium-length documents,

- Providing feedback on documents,  
- Answering questions about a document, or  
- Generating questions a user might want to ask about a document.

## E2 – Exposure by LLM-powered applications

Label tasks E2 if access to the LLM alone may not halve the time required to complete the task, but one can readily envisage supplementary software that could be developed atop the LLM to halve the task completion time. This software might feature capabilities like:  
- Summarising documents exceeding 2000 words and fielding questions about those documents  
- Collecting current facts from the Internet and integrating those facts with LLM functionalities  
- Scanning an organisation's extant knowledge, data, or documents and extracting information

Examples of software developed atop the LLM that may assist in completing employee tasks include:  
- Software created for a home goods company that rapidly processes and summarises their current internal data in customised ways to support product or marketing strategies.  
- Software capable of proposing real-time responses for customer service representatives engaging with customers through the company's customer service platform.  
- Software devised for legal purposes that can swiftly collate and summarise all prior cases in a specific legal domain and compose legal research briefs suited to the solicitor's firm requirements.  
- Software tailor-made for educators that enables them to enter a marking scheme and upload the text files of all student essays, with the software generating a letter grade for each essay.  
- Software that retrieves current facts from the internet and employs the capabilities of the LLM to produce news digests in various languages.

## E3 – Exposure Given Image Capabilities

Assume you possess access to both the LLM and a system capable of viewing, captioning, and generating images. However, this system is unable to process video media as inputs. Moreover, this system is not precise in extracting highly detailed information from image inputs, for instance, measuring dimensions within an image. Label tasks as E3 if there is a considerable reduction in the time required to complete the task with access to an LLM and these image functionalities:  
  
- Extracting text from PDFs,  
- Scanning images, or  
- Producing or altering digital images as per directives.

## Examples of annotations:

Occupation: Inspectors, Testers, Sorters, Samplers, and Weighers  
Task: Adjust, clean, or repair products or processing equipment to rectify defects identified during inspections.  
Label (E0/E1/E2/E3): E0  
Explanation: The model lacks any form of physical presence, and over half of the tasks described (adjusting, cleaning, and repairing equipment) necessitate the use of hands or a physical embodiment.

Occupation: Computer and Information Research Scientists  
Task: Apply theoretical expertise and innovation to create or apply new technology, such as adapting principles for applying computers to new uses.  
Label (E0/E1/E2/E3): E1  
Explanation: The model can acquire theoretical expertise during training as part of its general knowledge base, and the principles for adaptation can be captured in the text input to the model.

Activity: Schedule dining reservations. Label (E0/E1/E2/E3): E2 Explanation: Automation technology already exists for this (e.g., Resy), and it’s unclear what an LLM offers on top of using that technology (no-diff). That said, you could build something that allows you to ask the LLM to make a reservation on Resy for you. (E3)

Activity: Negotiate purchases or contracts. Label (E0/E1/E2/E3): E2 Explanation: Each party could document their perspective and then input this into an LLM to settle any disagreements (E3). However, widespread adoption of new technological tools would be necessary to achieve this (system).

Occupation: Allergists and Immunologists  
Task: Prescribe medication such as antihistamines, antibiotics, and nasal, oral, topical, or inhaled glucocorticosteroids.  
Label (E0/E1/E2/E3): E2  
Explanation: The model can offer conjectures for various diagnoses and write prescriptions and case notes. Nevertheless, it continues to necessitate a human in the loop applying their discernment and expertise to make the ultimate decision.

Output list with items "index: {TaskID} label: {label} explanation: {5-word explanation}" separated by ";"

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