Analysis
2024:02
8th February 2024

Large language models and the Danish labour market

By Ole Teutloff*, Johanna Einsiedler** and Fenja Søndergaard Møller

Generative artificial intelligence (AI) tools such as large language models are spreading rapidly. The most prominent example is ChatGPT, which gathered more than 100 million active users within two months. This type of generative AI has the potential to change the way people work, creating opportunities for innovation and productivity gains. However, the opportunities and challenges will most likely be unequally distributed across the workforce.

This analysis explores the unequal economic impact of large language models (LLMs) on the Danish Labour Market. The analysis uses the so-called AI Occupational Exposure (AIOE) scores from a study of the American labour market and merges these scores with administrative data from Statistics Denmark. The AIOE scores reflect the relatedness between AI applications and human abilities connected to different occupations. Thus, the scores express potential economic impact of AI applications across occupations through either labour-augmenting or labour-displacing effects.

Main conclusions:

- Occupations dominated by cognitive routine tasks have the highest potential to change through large language models. *Legal Professionals* is the occupation with the highest LLM score. The occupation with the lowest score is *Painters, building structure cleaners & related trades worker*.
- Economic activities influenced by cognitive abilities have higher LLM scores than activities dominated by physical tasks. The activity with the highest LLM score is *Higher Education*. The activity with the lowest score is *Building completion and finishing*.
- Employed females altogether have more potential to apply large language models than employed males. However, within *Human Health & Social Work activities* women have a slightly lower LLM score than males.
- Employees with high personal yearly income generally have more potential to use and take advantage of large language models than employees with lower income.

* Ole Teutloff is affiliated with Copenhagen Center for Social Data Science – SODAS, University of Copenhagen and Center for Collective Learning, University of Toulouse.
** Johanna Einsiedler is affiliated with Copenhagen Center for Social Data Science – SODAS, University of Copenhagen.

Cognitive routine tasks have the highest potential to change

Over the last couple of years, the capabilities of generative artificial intelligence (AI) have increased in a variety of domains. Specifically large language models (LLMs), which are programs developed to extract meaning from texts (input) and generate text (output), have been on the rise. One of the most recent examples is generative pre-trained transformers (GPT) such as ChatGPT released by OpenAI in November 2022. Since its launch, ChatGPT has gained users at enormous speed and has now reached more than 100 million users globally. This dramatic increase in users of LLMs might generate noticeable opportunities for augmenting and displacing human labour and thus influence the composition of the labour market. Occupations dominated by cognitive routine tasks are likely to experience the largest changes.

Felten et al. (2023)[1] developed a method to assign so-called AI Occupational Exposure (AIOE) scores to different occupations and industries. The score represents an estimate of the relatedness between human abilities and different AI applications. The score is agnostic to whether AI will complement, change or replace human labour. It can be understood as a measure for potential economic impact without specifying the nature of the effect (human-augmenting vs. human-displacing). The scores are standardised and expressed relative to the average of all officially recognised American occupations. Box 1 provides a detailed description of the AIOE scores. This analysis adapts the LLM scores developed by Felten et al. (2023) to the Danish context.[2] The analysis uncovers the unequal potential to use and possibly benefit from LLMs across occupations, activities, gender, income, education levels and municipalities in Denmark.

Figure 1 shows the occupations with the ten highest and lowest LLM scores, respectively. The list is based on the scores from Felten et al. 2023 merged with The Danish Work Classification Module and distributed by the Danish DISCO-08 classification on level 3, cf. box 2. The occupation that has the highest LLM score is *Legal Professionals*, followed by *Universities and higher education teachers*. These occupations are dominated by cognitive work. 26,400 Danish employees worked as *Legal Professionals*, whereas 39,400 worked as *Universities and higher education teachers* in 2021. The occupations that have the lowest LLM scores are *Painters, building structure cleaners & related trades workers* and *Mining and construction labourers*. These are occupations dominated by physical abilities and craftsmanship.[3] Appendix 1 provides the full list of occupations and their LLM scores.

---

1 See Felten, Edward W. & Raj, Manav & Seamans, Robert (March 2023): How will Language Modelers like ChatGPT Affect Occupations and Industries? and Felten, Edward W. & Raj, Manav & Seamans, Robert (2021): Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses, *Strategic Management Journal*, John Wiley & Sons Ltd.

2 The authors of this analysis have also looked into AIOE scores of image models in a Danish context. The AIOE scores of image models provide similar results.

3 15,800 employees in the Danish labour market worked as *Painters, building structure cleaners & related trades workers* and 45,700 worked as *Mining and construction labourers* in 2021. In 2021, *Personal care workers in health services* was the occupation with most Danish employees (170,900 persons). This occupation has the 60th highest LLM score among the 113 distinct occupations on the DISCO level 3 with 1,000 or more workers.

Figure 1 Top-10 Danish occupations with highest LLM scores and bottom-10 occupations with lowest scores (DISCO-08, level 3).

Note: Aggregated on level 3 (126 distinct occupations) of DISCO-08. 13 occupations were excluded because less than 1,000 persons work in that occupation or because Felten et al. (2023) do not provide an AIOE score for that occupation.
Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023).

Tools like ChatGPT excel at supporting cognitive tasks such as writing or programming. In contrast, ChatGPT offers little help when painting an apartment or paving a road. As a result, occupations that rely heavily on cognitive abilities have greater potential to benefit from LLM technologies. To illustrate how differences in abilities translate into differences in LLM scores, consider the following example: Legal professionals such as judges have one of the highest LLM scores, cf. figure 1. Some of their most important abilities are written comprehension and written expression, deductive and inductive reasoning, and oral comprehension. All of these abilities are cognitive abilities with medium to high LLM score, resulting in a high overall score for legal professionals. In practice, legal professionals could use LLMs for many tasks such as summarizing texts, looking up laws and court cases or drafting letters. Construction workers, on the other hand, have one of the lowest LLM scores. Construction workers require abilities such as manual dexterity, trunk strength, stamina, and arm-hand steadiness. Software tools such as ChatGPT are of little relevance for these types of physical or psychomotor skills: Predicting the next word in a sentence does not yet help with building walls, roofs and roads.

Cognitive abilities correlate with most factors in this analysis. Occupations high in cognitive abilities tend to be well paid, require longer education and concentrate in urban areas. As a result, differences in cognitive abilities drive large parts of the findings presented in the following sections.

Box 1. AI Occupational Exposure (AIOE) scores

The analysis adopts the AI Occupational Exposure (AIOE) scores developed by Felten et al. (2021). The scores cover ten AI applications defined by the Electronic Frontier Foundation (EFF). These applications include translation, image generation, visual question answering, language modelling etc. Following Felten et al. (2023), this analysis focuses on *language modelling* which is the AI application most closely related to the recent boom in generative AI.

AI-applications are linked to occupations via data on human abilities from the Occupational Information Network (O*NET) database developed by the United States Department of Labor. The O*Net database categorises abilities into cognitive, physical, psychomotor and sensory abilities, and uses 52 human abilities (such as oral expression, oral comprehension, speed of limb movement, static strength etc.) to describe more than 800 specific occupations. Each of the occupations can be thought of as a weighted combination of the 52 human abilities. O*NET uses two sets of weights: prevalence and importance. Felten et al. (2021) weight the ability-level AIOE by the ability's prevalence and importance within each occupation as measured by O*NET. Through a survey (approximately 2.000 respondents) on Amazon Mechanical Turk (MTurk), Felten et al. created a measure of relatedness between the AI application domains and the 52 O*NET abilities. The AIOE scores are standardised across occupations with mean zero and standard deviation one. Thus, positive values indicate that an occupation is exposed to LLMs more than the average occupation listed in O*NET.

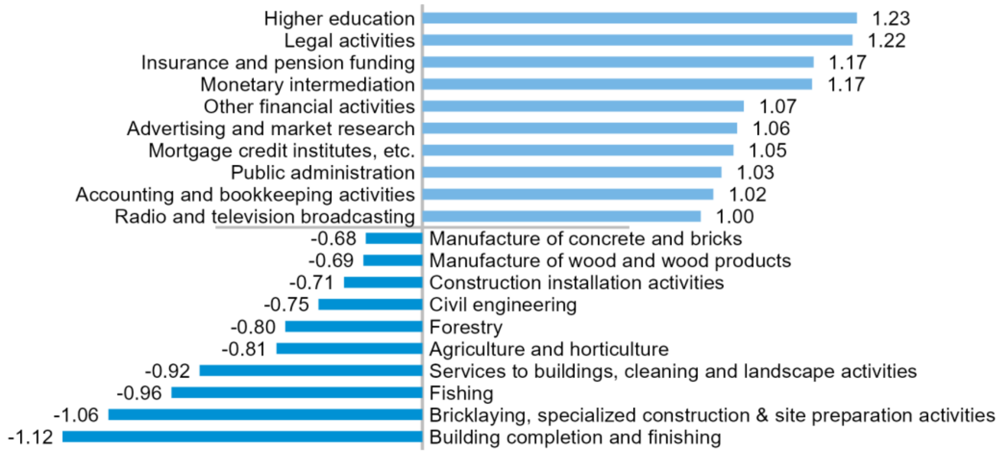
The AIOE scores have several limitations. The MTurk data might suffer from annotator bias, as the scores depend on the respondents' perception of technological progress at the time of the data collection (2021) and their understanding of how AI could be used at work. As a result, respondents may only partly recognize or anticipate new creative or unconventional ways of using AI. Studying AI is like trying to hit a moving target, as the capability of AI technology is constantly evolving and advancing. For example, the score does not include the most recent advances in generative AI, such as the integration of image capabilities into the LLM GPT-4. Moreover, it is difficult to grasp the size of the impact of generative AI on the daily routines of specific occupations. Lastly, it is important to highlight that the AIOE scores do not differentiate between enhancement and replacement. LLMs could make human labour more efficient, i.e. reduce time required for a human to perform a specific task. Other tasks might be completed entirely by LLM systems. Yet, jobs normally consist of bundles of diverse tasks. As of now, there are most likely few occupations for which AI tools could take over all the work. The precise labour market outcomes are uncertain because they will depend on a mix of technical feasibility, policy regulations and the overall situation of the economy.

Higher Education is the activity with highest LLM score

This section describes how LLM scores vary across different economic activities, i.e. the statistical classification of different types of activities commonly referred to as industries. Whereas *occupations* concern the specific positions such as construction labourers, the categorization of *activities* concern the whole activity such as roofing activities.

Figure 2 shows the top-10 and bottom-10 economic activities that have the lowest and highest LLM scores, respectively. The scores are based on an average of the LLM scores of all the employees[4] in the specific activities (standard group-127 of DB07, the Danish version of NACE, cf. box 2). The activity with the highest scores is *Higher Education* followed by *Legal Activities*. This reflects that these activities have a large share of employees in occupations dominated by cognitive abilities. In 2021, there were 58,500 employees in Denmark working in *Higher Education* and 10,700 in *Legal Activities*. The activities with the lowest scores are *Building completion and finishing* and *Bricklaying and other specialized construction activities and site preparation activities*. Around 54,700 people worked in *Building completion and finishing* in Denmark in 2021 and 30,200 in *Bricklaying and other specialized construction activities and site preparation activities.* Both of these activities are dominated by physical tasks that are hard to complement with large language models. Appendix 2 provides the full list of activities and LLM scores.

Figure 2 Top-10 activities with highest LLM scores and bottom-10 activities with lowest LLM scores



Notes: Aggregated to standard group-127. 6 activities with less than 1,000 workers were excluded.

Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023)

[4] The average LLM score across activities is based on the individual unweighted scores for the employees in the specific activities. Only the employment that generates the person's main source of income in 2021 is included. The average score does not take into account that some of the employees work part time (or less).

Box 2. Administrative data from Statistics Denmark

The LLM scores are combined with detailed Danish administrative data on the labour market status from 2021 (Work Classification Module). Among others, this register contains information on occupations (DISCO-08) and the economic activities of companies (DB07). DISCO-08 is the official Danish version of the international classification, International Standard Classification of Occupations (ISCO-08). DB07 is the Danish version of the statistical classification of economic activities in the European Community (NACE), and the analysis uses the activity codes from the Danish standard group-127.

The population is limited to employees who had active employment in Denmark in the year 2021 and where we know the DISCO-08 code. In total, the population covers 2.7 million persons, including employees, self-employed people and assisting spouses. Moreover, the analysis only covers the employment that generates the persons' main source of income in 2021.

The O*NET database is directly based on the 2010 Standard Occupational Classification System (SOC-2010) from the U.S. Bureau of Labor Statistics. Felten et al. (2023) provide AIOE scores for 774 different SOC-2010 occupations. For this analysis, we matched the SOC-2010 occupations to ISCO-08 codes. Out of 438 ISCO occupations, there are AIOE scores available for 374 occupations. 155 of those are matched to exactly one SOC occupation; the remaining ones are assigned the mean AIOE score of all matching SOC occupations. After matching those to Danish Labour Market data, it is possible to assign AIOE scores to 89 pct. of all people having active employment in Denmark in 2021 (and with a known DISCO-08 code). 4 pct. of the missing observations concern special Danish codes for *Pedagogical work* or *Specialized pedagogical work*. These observations are matched with *Child care workers* and *Teaching professionals not elsewhere classified*, respectively. The remaining 7 pct. concern i) observations that have successfully been matched to an SOC occupation, but where Felten et al. (2023) do not provide an AIOE score for that occupation and ii) ISCO codes with missing observations on lower levels. These observations are not included in the analysis.

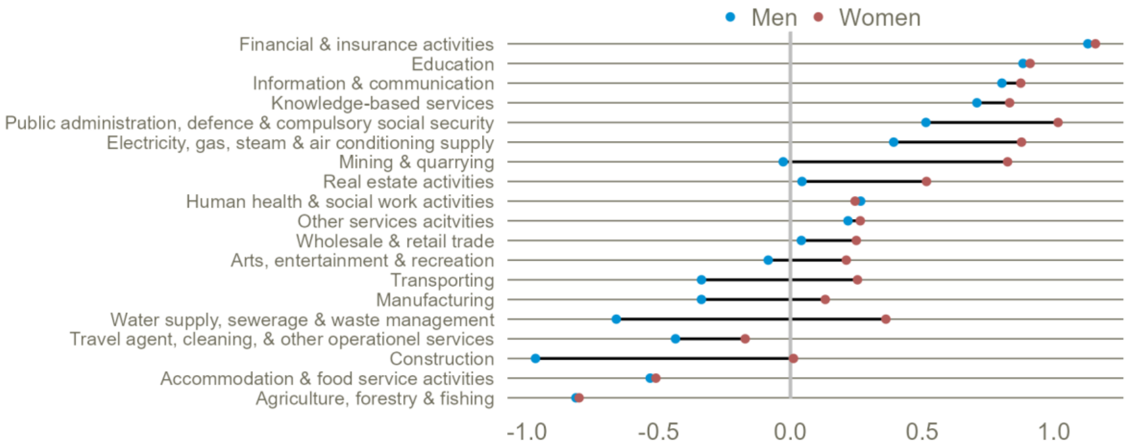
The labour market data is merged with additional registry data on gender, age, and municipality of residency from the Population Register, income from the Income Register and educational attainment from the Education Attainment Register.

Females have higher LLM scores than males

Females have higher LLM scores than males.[5] In general, this reflects that to a great extent, females work in occupations dominated by cognitive tasks rather than physical abilities – at least to a greater extent than males. However, this is not the case across all activities. In the activity *Human health & social work activities,* females have slightly lower LLM scores than males, cf. figure 3. This could reflect that females in this activity have more practical positions such as nurses and social workers, whereas males work in management or other positions, where less practical skills dominate. Nonetheless, figure 3 illustrates that females have higher LLM scores in all the other 18 activities. This divergence is particularly large within *Construction* and *Water supply, sewerage, waste management*.

[5] The overall LLM score for females is 0.43 standard deviations higher than for males.

Figure 3 Absolute differences in LLM scores by gender within each activity (level 1)

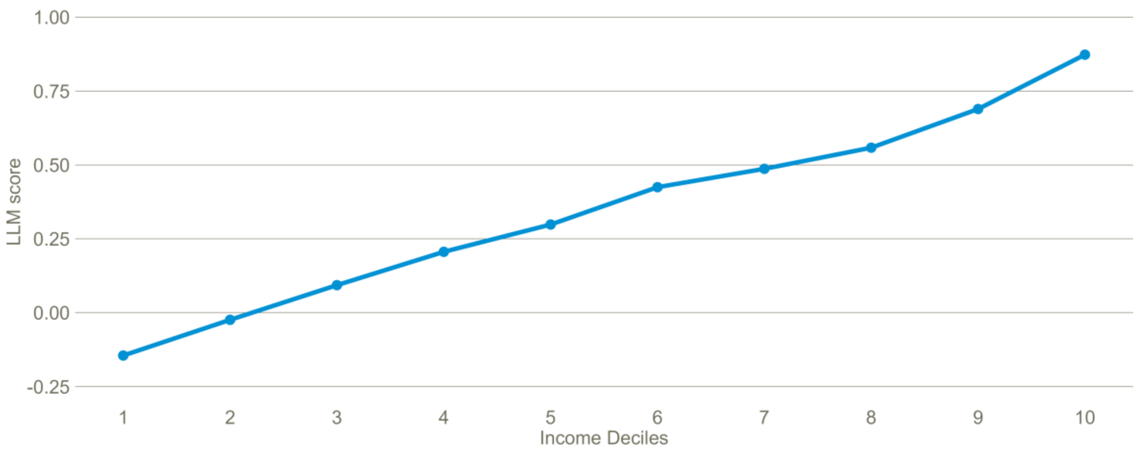


Notes: Aggregated on level 1 (standard group-19). Aggregation on other levels show fairly the same patterns.
Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023)

Occupations with higher earnings have higher LLM scores

Figure 4 illustrates the LLM scores for income deciles for full-time employees that are at least 25 years old.[6] Employees with high personal yearly incomes have higher LLM scores than employees with low incomes.[7] This relationship is as expected, since occupations that are high in cognitive abilities tend to be well paid. Moreover, only the first two deciles have negative LLM scores. This is due to the structure of the Danish labour market: Compared to the U.S., more people work in high-skilled occupations (see Appendix 3 Figure A). The relationship between income and LLM score is fairly constant across age groups.[8]

Figure 4 LLM scores by income for full-time employees are at least 25 years.



Source: The Work Classification Module 2021 and the Income Register combined with LLM scores from Felten et al. (2023)

[6] Full-time employees include people that have worked 1664 or more hours per year (i.e. minimum of 32 hours per week). This cutoff point is normally used to distinguish between full-time jobs and part-time jobs (see HELTID_32_KODE) and make the incomes more comparable across individuals. Furthermore, the population is limited to people that are at least 25 years old, that is when most people have finished their education. Nonetheless, the main conclusions are robust to alternative cutoff points and age limits.

[7] Personal income covers all the personal income in total, including primary income, public transfer income and some capital income. Moreover, The Work Classification Module covers the total yearly income. Find more information about income at the DST website.

[8] Looking solely at age, the youngest age groups (18-30 years) tend to have lower LLM scores than the older groups. Between the age of 30 and 45, scores are fairly constant. From the age of 45, the LLM scores decrease with increasing age.

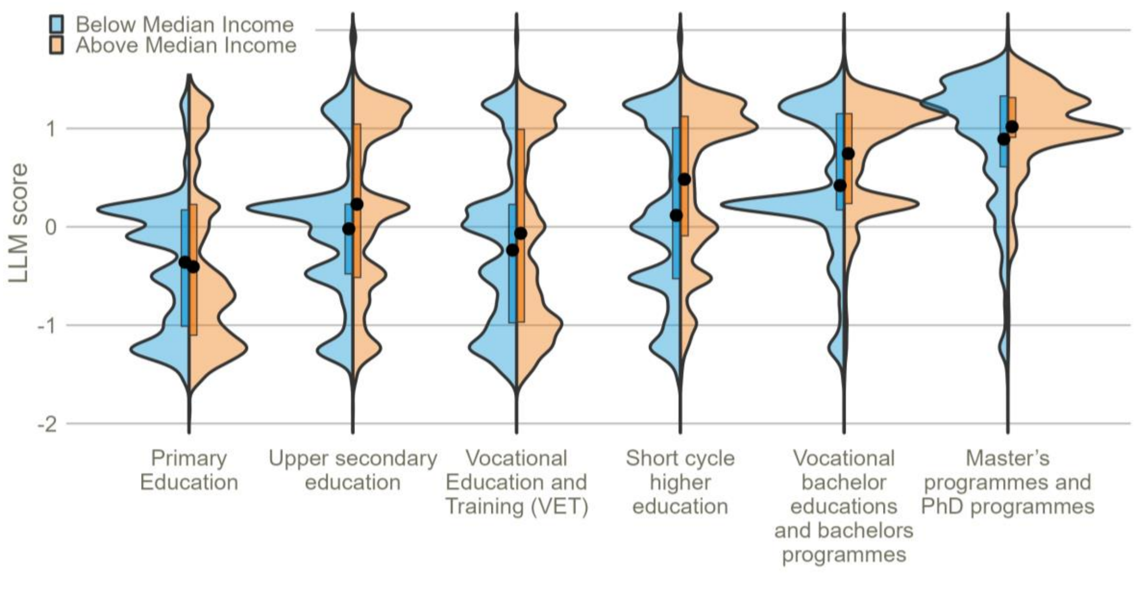
Employees with master's degrees have higher LLM scores

Employees with completed *Master's programmes and PhD programmes* tend to have higher LLM scores than employees with lower level educational attainment[9] such as *Primary education* and *Upper secondary education*. However, the average LLM scores do not vary much across the lower level educational categories. In addition, the dispersion is large within the different educational levels. For instance, the LLM scores vary from -1.85 to 1.93 within the category of *Vocational education*. This means that the *Vocational educations* lead to occupations that have both higher and lower scores than the average occupation in the O*NET framework.

Figure 5 compares the distribution of LLM scores for low and high income earners within each education level. The figure shows a high variation in the scores, in particular for people with educational attainment in the groups below *Master's programmes and PhD programmes.* The wide dispersion indicates that people in these educational groups both work in occupations that are only marginally related to LLMs but *also* in occupations with high LLM scores. For example, within the five largest occupational groups (level 3) for individuals without a university degree, there are three occupations with comparatively low LLM scores: *Personal care workers in health services* (-0.14), *Domestic, hotel and office cleaners and helpers* (-1.22) *and Building frame and related trades workers* (-1.28) but also two with LLM scores above the average; *Shop salespersons* (0.20) and *General office clerks* (1.25).

However, within the group of people with higher educational attainment, there is a positive relationship between the educational attainment and LLM scores: Individuals with a master's degree or PhD are more concentrated in jobs with high scores than individuals with a bachelor's degree.

Figure 5 **Distribution of LLM scores by education and income**



Notes: The dots mark the average LLM scores for the different educational levels. The surrounding boxes mark 25th and 75th percentiles of the distribution, i.e. 50 pct. of the population falls within the marked range.

Source: The Education Attainment Register, the Work Classification Module 2021, and the Income Register combined with LLM scores from Felten et al. (2023)

Figure 5 also shows the distributions of LLM scores divided according to two income groups; below and above the median income. Patterns are roughly similar for low-income earners (below

[9] Employees are grouped according to their highest educational attainment in 2021 based on the UDD Classification level 1. For this analysis we did some further aggregation: *Preparatory Education* (15), *Upper Secondary Education* (20) and *Danish lessons at language centres* (25) were combined to *Upper secondary education*. *Vocational Education* (30) and *Qualifying courses* (35) were labelled as *Vocational Education and Training (VET)*. *Medium-term higher education* (50) and *Bachelor education* (60) were combined into *Vocational bachelor educations and bachelor programmes*. *Long-term higher education* (70) and *PhD or research education* (80) were jointly named *Master's programmes and PhD programmes*.

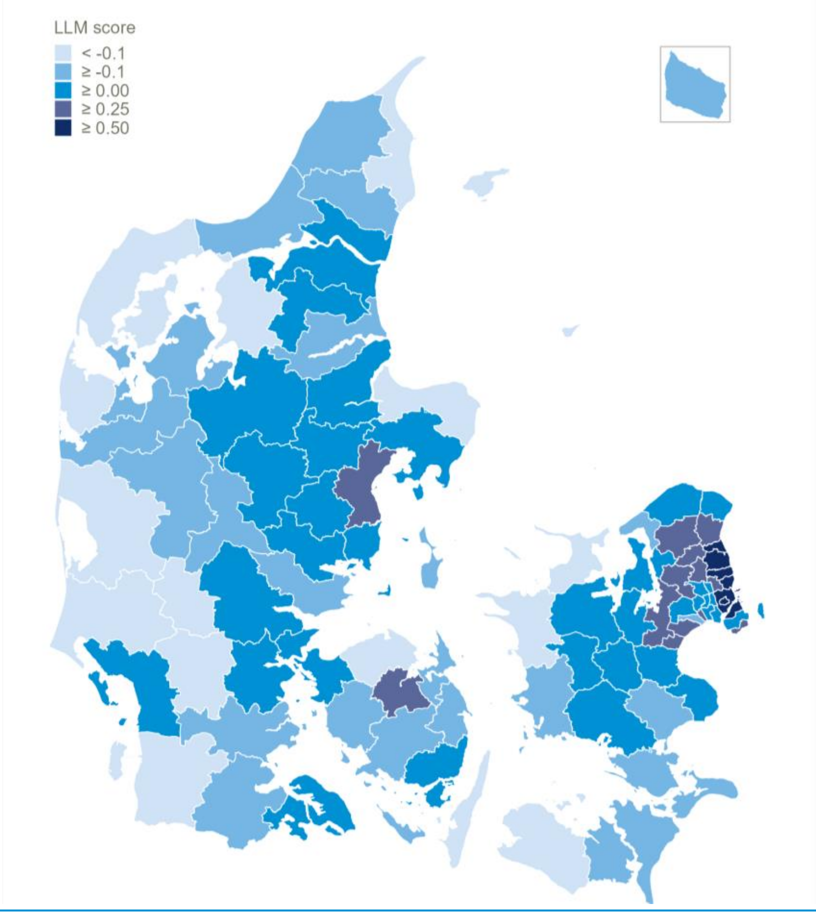
median) and high-income earners within each education. Nonetheless, the group with income above the median has a higher score on average across the different educational levels – with primary education as the exception.

Urban municipalities have higher LLM scores

As expected, the LLM scores vary across municipalities.[10] Figure 6 shows that municipalities in the capital region and municipalities that include big cities (Odense, Kolding, Vejle, Aarhus, Skanderborg, Silkeborg and Aalborg) stand out with higher-than-average scores. This pattern is confirmed when examining the relationship between the average LLM scores and the population density of a municipality, as these two factors are strongly correlated.[11]

The geographical differences are mainly driven by the variation in occupation types. Occupations high in cognitive abilities tend to concentrate in urban areas – like they tend to be well paid and require longer education. This is shown in the DST Analysis concerning income and education in urban areas.

Figure 6 LLM scores per municipality



Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023)

[10] This section is based on municipality of residence. However, using the municipality of the workplace and enterprise shows similar results.

[11] A 1 pct. increase in population density is associated with a 0.13 increase in the LLM score. The correlation coefficient of population density and LLM score is 0.54.

About the analysis

Large language models and the Danish labour market
Published: 8th February 2024 by Statistics Denmark
No. 2024:02
ISSN: 2446-0354

Fenja Søndergaard Møller
Telephone: +45 23 62 62 99
Email: fsm@dst.dk

Appendix 1. LLM scores and occupation

No.	Occupation title	Occupation DICSO code	Mean LLM score	Number of people working in the occupation in Denmark in 2021
1	Legal professionals	261	1.59	26 379
2	University and higher education teachers	231	1.52	39 440
3	Social and religious professionals	263	1.31	44 194
4	Authors, journalists and linguists	264	1.30	13 702
5	Finance professionals	241	1.27	44 865
6	Other teaching professionals	235	1.27	53 217
7	Secretaries (general)	412	1.25	7 582
8	General office clerks	411	1.25	120 508
9	Secondary education teachers	233	1.25	16 290
10	Administration professionals	242	1.24	23 484
11	Sales, marketing and public relations professionals	243	1.24	27 818
12	Mathematicians, actuaries and statisticians	212	1.22	2 009
13	Sales, marketing and development managers	122	1.20	15 455
14	Client information workers	422	1.12	24 456
15	Sales and purchasing agents and brokers	332	1.11	51 547
16	Numerical clerks	431	1.11	24 265
17	Administrative and specialized secretaries	334	1.10	30 741
18	Business services and administration managers	121	1.07	26 866
19	Professional services managers	134	1.06	15 036
20	Software and applications developers and analysts	251	1.00	57 853
21	Managing directors and chief executives	112	0.99	24 887
22	Financial and mathematical associate professionals	331	0.98	33 735
23	Legislators and senior officials	111	0.98	1 944
24	Information and communications technology service managers	133	0.95	3 434
25	Medical doctors	221	0.93	28 463
26	Other services managers	143	0.89	2 097
27	Engineering professionals (excluding electrotechnology)	214	0.87	51 690
28	Business services agents	333	0.79	29 489
29	Electrotechnology engineers	215	0.74	7 574
30	Physical and earth science professionals	211	0.73	3 392
31	Database and network professionals	252	0.73	10 313
32	Primary school and early childhood teachers	234	0.70	161 924
33	Retail and wholesale trade managers	142	0.68	8 601
34	Librarians, archivists and curators	262	0.64	3 569
35	Life science professionals	213	0.62	6 391
36	Legal, social and religious associate professionals	341	0.62	11 168
37	Architects, planners, surveyors and designers	216	0.58	13 526
38	Manufacturing, mining, construction, and distribution managers	132	0.55	14 589
39	Regulatory government associate professionals	335	0.54	9 695
40	Vocational education teachers	232	0.49	14 030
41	Creative and performing artists	265	0.47	6 908
42	Other health professionals	226	0.45	43 986
43	Other personal services workers	516	0.43	9 994
44	Other clerical support workers	441	0.40	34 083
45	Information and communications technology operations and user support technicians	351	0.40	14 634
46	Tellers, money collectors and related clerks	421	0.37	3 178
47	Other sales workers	524	0.33	30 102
48	Nursing and midwifery professionals	222	0.24	71 488
49	Child care workers and teachers' aides	531	0.23	65 872
50	Keyboard operators	413	0.21	2 239
51	Shop salespersons	522	0.20	141 240
52	Hotel and restaurant managers	141	0.18	1 552
53	Telecommunications and broadcasting technicians	352	0.08	4 025
54	Material-recording and transport clerks	432	0.03	35 825
55	Travel attendants, conductors and guides	511	0.01	4 595
56	Physical and engineering science technicians	311	-0.04	57 387
57	Veterinarians	225	-0.08	2 548
58	Cashiers and ticket clerks	523	-0.11	53 523

59	Medical and pharmaceutical technicians	321	-0.13	18 905
60	Personal care workers in health services	532	-0.14	170 857
61	Production managers in agriculture, forestry and fisheries	131	-0.16	1 344
62	Hairdressers, beauticians and related workers	514	-0.18	13 254
63	Artistic, cultural and culinary associate professionals	343	-0.18	6 852
64	Nursing and midwifery associate professionals	322	-0.23	1 023
65	Ship and aircraft controllers and technicians	315	-0.23	5 907
66	Other health associate professionals	325	-0.27	15 571
67	Other craft and related workers	754	-0.39	3 180
68	Protective services workers	541	-0.42	26 571
69	Veterinary technicians and assistants	324	-0.44	1 055
70	Sports and fitness workers	342	-0.44	5 236
71	Process control technicians	313	-0.45	3 315
72	Waiters and bartenders	513	-0.45	17 479
73	Printing trades workers	732	-0.47	3 641
74	Cooks	512	-0.53	14 476
75	Transport and storage labourers	933	-0.54	50 227
76	Electronics and telecommunications installers and repairers	742	-0.61	2 378
77	Handicraft workers	731	-0.65	3 029
78	Heavy truck and bus drivers	833	-0.66	42 061
79	Car, van and motorcycle drivers	832	-0.73	10 210
80	Other elementary workers	962	-0.73	18 195
81	Animal producers	612	-0.75	8 859
82	Food processing and related trades workers	751	-0.78	13 732
83	Food and related products machine operators	816	-0.80	19 752
84	Locomotive engine drivers and related workers	831	-0.83	3 007
85	Assemblers	821	-0.84	16 049
86	Refuse workers	961	-0.85	2 531
87	Mixed crop and animal producers	613	-0.91	3 868
88	Blacksmiths, toolmakers and related trades workers	722	-0.93	32 875
89	Other stationary plant and machine operators	818	-0.94	11 836
90	Garment and related trades workers	753	-0.94	1 612
91	Electrical equipment installers and repairers	741	-0.96	32 186
92	Machinery mechanics and repairers	723	-0.96	28 428
93	Chemical and photographic products plant and machine operators	813	-0.98	4 865
94	Market gardeners and crop growers	611	-1.00	18 699
95	Mobile plant operators	834	-1.01	8 427
96	Food preparation assistants	941	-1.04	41 898
97	Building and housekeeping supervisors	515	-1.04	27 072
98	Mining and mineral processing plant operators	811	-1.08	2 543
99	Forestry and related workers	621	-1.08	1 624
100	Rubber, plastic and paper products machine operators	814	-1.09	9 198
101	Building finishers and related trades workers	712	-1.15	23 973
102	Wood treaters, cabinet-makers and related trades workers	752	-1.18	2 999
103	Metal processing and finishing plant operators	812	-1.20	7 840
104	Domestic, hotel and office cleaners and helpers	911	-1.22	75 381
105	Textile, fur and leather products machine operators	815	-1.23	1 102
106	Wood processing and papermaking plant operators	817	-1.24	5 124
107	Sheet and structural metal workers, moulders and welders, and related workers	721	-1.25	12 521
108	Manufacturing labourers	932	-1.26	27 838
109	Building frame and related trades workers	711	-1.28	64 709
110	Agricultural, forestry and fishery labourers	921	-1.34	4 951
111	Vehicle, window, laundry and other hand cleaning workers	912	-1.37	9 408
112	Mining and construction labourers	931	-1.44	45 668
113	Painters, building structure cleaners and related trades workers	713	-1.47	15 810

Note: Aggregated on level 3 (126 distinct occupations) of DISCO-08. 13 occupations were excluded because less than 1,000 persons work in that occupation or because Felten et al. (2023) do not provide an AIOE score for that occupation.

Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023).

Appendix 2. LLM scores and activities

No.	Activity title	Activity code	Mean LLM Score	Number of people working in the industry in Denmark in 2021
1	Higher education	85.00.3	1.23	58 467
2	Legal activities	69.00.1	1.22	10 724
3	Insurance and pension funding	65.00.0	1.17	21 210
4	Monetary intermediation	64.00.1	1.17	38 299
5	Other financial activities	66.00.0	1.07	9 405
6	Advertising and market research	73.00.0	1.06	10 893
7	Mortgage credit institutes, etc.	64.00.2	1.05	10 349
8	Public administration	84.00.1	1.03	89 214
9	Accounting and bookkeeping activities	69.00.2	1.02	19 962
10	Radio and television broadcasting	60.00.0	1.00	5 778
11	Publishing of computer games and other software	58.00.2	0.93	6 246
12	Information technology service activities	62.00.0	0.92	45 772
13	Travel agent activities	79.00.0	0.89	2 838
14	Information service activities	63.00.0	0.86	7 025
15	Primary education	85.00.1	0.83	106 616
16	Wholesale on a fee or contract basis	46.00.1	0.82	3 000
17	Adult and other education	85.00.4	0.81	23 023
18	Other technical business services	74.00.0	0.77	10 219
19	Secondary education	85.00.2	0.74	52 771
20	Business consultancy activities	70.00.0	0.73	27 293
21	Wholesale of IT-equipment	46.00.5	0.73	11 153
22	Scientific research and development	72.00.0	0.72	17 791
23	Publishing	58.00.1	0.69	13 196
24	Telecommunications	61.00.0	0.67	13 971
25	Renting of non-residential buildings	68.00.3	0.65	7 500
26	Production and distribution of electricity	35.00.1	0.65	8 290
27	Activities of membership organizations	94.00.0	0.61	31 261
28	Other business service activities	82.00.0	0.57	15 952
29	Wholesale of textiles and household goods	46.00.4	0.56	41 325
30	Architectural and engineering activities	71.00.0	0.56	43 154
31	Gambling and betting activities	92.00.0	0.50	1 476
32	Extraction of oil and gas	06.00.0	0.47	1 323
33	Motion picture and television programme production, and sound recording activities	59.00.0	0.47	5 395
34	Manufacture of other electronic products	26.00.2	0.43	12 313
35	Pharmaceuticals	21.00.0	0.43	28 371
36	Libraries, museums and other cultural activities	91.00.0	0.43	14 532
37	Retail sale of consumer electronics	47.00.4	0.42	3 170
38	Manufacture and distribution of gas	35.00.2	0.40	1 074
39	Water transport	50.00.0	0.38	7 811
40	Buying and selling of real estate	68.00.1	0.34	13 175
41	Other specialized wholesale	46.00.7	0.32	40 224
42	Medical and dental practice activities	86.00.2	0.31	71 790
43	Hospital activities	86.00.1	0.30	132 254
44	Mining support service activities	09.00.0	0.27	1 688
45	Manufacture of toys and other manufacturing	32.00.2	0.26	6 252
46	Social work activities without accommodation	88.00.0	0.24	215 033
47	Defence, public order, security and justice activities	84.00.2	0.24	34 734
48	Wholesale of other machinery	46.00.6	0.22	28 559
49	Retail sale of wearing apparel	47.00.7	0.20	19 562
50	Residential care activities	87.00.0	0.19	152 226
51	Manufacture of medical instruments, etc.	32.00.1	0.18	5 654
52	Retail sale of cultural and recreation goods, etc.	47.00.6	0.18	9 194
53	Manufacture of basic chemicals	20.00.1	0.15	4 880
54	Retail sale of textiles and household equipment, etc.	47.00.5	0.13	56 863
55	Theatres, concerts, and arts activities	90.00.0	0.12	5 647
56	Wholesale of food, beverages and tobacco	46.00.3	0.11	19 276
57	Wholesale of cereals and feeding stuffs	46.00.2	0.08	2 799
58	Retail sale via Internet, mail order, etc.	47.00.8	0.07	11 345
59	Manufacture of computers and communication equipment etc.	26.00.1	0.06	4 427
60	Support activities for transportation	52.00.0	0.05	29 267
61	Manufacture of engines, windmills and pumps	28.00.1	0.05	25 994
62	Supermarkets and department stores, etc.	47.00.1	0.04	126 966
63	Rental and leasing activities	77.00.0	0.04	6 384
64	Manufacture of paints and soap etc.	20.00.2	0.03	8 542
65	Retail sale of food in specialized stores	47.00.2	0.03	6 951
66	Manufacture of wearing apparel	14.00.0	0.01	1 517

67	Security and investigation activities	80.00.0	0.00	5 641
68	Air transport	51.00.0	-0.03	4 133
69	Employment activities	78.00.0	-0.05	57 909
70	Steam and hot water supply	35.00.3	-0.09	1 281
71	Manufacture of household appliances, lamps, etc.	27.00.3	-0.09	4 302
72	Manufacture of wires and cables	27.00.2	-0.09	1 810
73	Other manufacture of food products	10.00.5	-0.10	11 379
74	Manufacture of electric motors, etc.	27.00.1	-0.11	4 317
75	Renting of real estate	68.00.2	-0.12	14 163
76	Passenger rail transport, interurban	49.00.1	-0.12	6 111
77	Printing etc.	18.00.0	-0.14	4 037
78	Veterinary activities	75.00.0	-0.15	3 245
79	Manufacture of grain mill and bakery products	10.00.4	-0.19	13 760
80	Manufacture of other machinery	28.00.2	-0.19	31 692
81	Manufacture of textiles	13.00.0	-0.21	2 790
82	Sports activities	93.00.1	-0.21	16 085
83	Manufacture of dairy products	10.00.3	-0.21	10 795
84	Manufacture of beverages	11.00.0	-0.23	3 435
85	Activity not stated	99.99.9	-0.24	8 371
86	Sale of motor vehicles	45.00.1	-0.25	23 760
87	Repair of personal goods	95.00.0	-0.25	2 341
88	Sewerage	37.00.0	-0.30	1 719
89	Other personal service activities	96.00.0	-0.31	18 094
90	Hotels and similar accommodation	55.00.0	-0.36	18 744
91	Manufacture of ships and other transport equipment	30.00.0	-0.37	2 842
92	Amusement and recreation activities	93.00.2	-0.38	4 795
93	Freight transport by road and via pipeline	49.00.3	-0.40	28 279
94	Retail sale of automotive fuel	47.00.3	-0.40	5 182
95	Processing and preserving of fish	10.00.2	-0.41	3 301
96	Manufacture of rubber and plastic products	22.00.0	-0.42	12 613
97	Transport by suburban trains, buses and taxi operation, etc.	49.00.2	-0.42	19 446
98	Postal and courier activities	53.00.0	-0.44	18 023
99	Manufacture of glass and ceramic products	23.00.1	-0.48	2 041
100	Manufacture of paper and paper products	17.00.0	-0.48	4 786
101	Repair and maintenance of motor vehicles etc.	45.00.2	-0.50	20 268
102	Extraction of gravel and stone	08.00.9	-0.53	1 092
103	Manufacture of furniture	31.00.0	-0.53	9 809
104	Repair and installation of machinery and equipment	33.00.0	-0.54	9 956
105	Waste management and materials recovery	38.00.0	-0.55	8 618
106	Production of meat and meat products	10.00.1	-0.56	15 890
107	Restaurants	56.00.0	-0.57	56 308
108	Manufacture of motor vehicles and related parts	29.00.0	-0.58	3 681
109	Manufacture of basic metals	24.00.0	-0.58	5 086
110	Manufacture of fabricated metal products	25.00.0	-0.62	32 455
111	Construction of buildings	41.00.0	-0.66	27 753
112	Manufacture of concrete and bricks	23.00.2	-0.68	13 019
113	Manufacture of wood and wood products	16.00.0	-0.69	9 183
114	Construction installation activities	43.00.1	-0.71	51 231
115	Civil engineering	42.00.0	-0.75	16 489
116	Forestry	02.00.0	-0.80	2 109
117	Agriculture and horticulture	01.00.0	-0.81	26 129
118	Services to buildings, cleaning and landscape activities	81.00.0	-0.92	66 386
119	Fishing	03.00.0	-0.96	1 045
120	Bricklaying and other specialized construction activities and site preparation activities	43.00.9	-1.06	30 209
121	Building completion and finishing	43.00.2	-1.12	54 697

Notes: Aggregated to standard group-127. 6 activities with less than 1,000 workers were excluded.

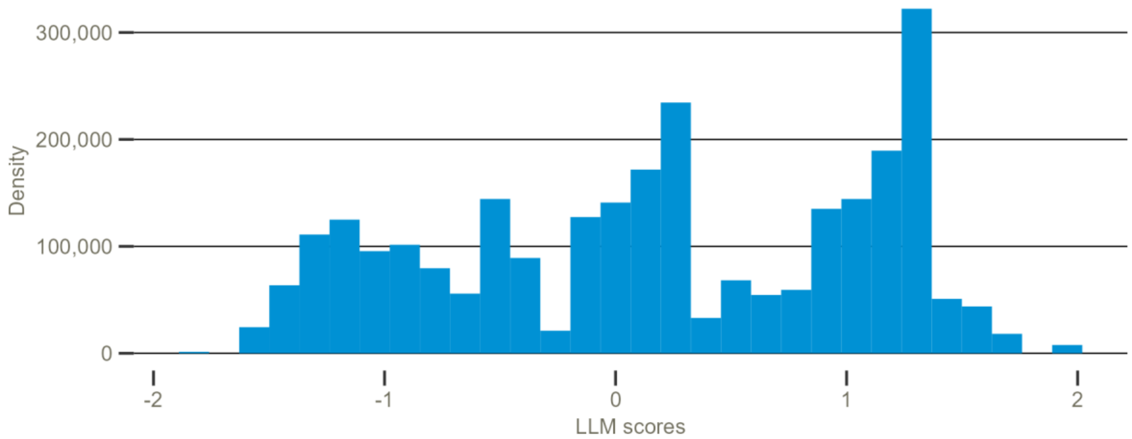
Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023)

Appendix 3. Distribution of the LLM scores

The AIOE scores are standardised across all occupations in the O*NET data. Thus, the average score corresponds to zero in the O*NET framework, while scores above zero, for instance, indicate higher AIOE scores than the average occupation in the O*NET data.

Figure A illustrates the distribution of the LLM scores for all people in Denmark who had active employment in 2021. The figure shows that a majority (61 pct.) of Danish employees work in occupations that have higher scores than the average occupation listed in O*NET data.

Figure A **Distribution of the LLM scores across all people employed in Denmark in 2021**



Source: The Work Classification Module 2021 combined with LLM scores from Felten et al. (2023)