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The Impact of Artificial Intelligence on the Labour Market

The impact of new technologies on the labour market has long been discussed throughout history as it often leads to significant social and economic change. Both positive and negative impacts are brought about, here we are discussing the impact on the labour market and the subsequent shift in wage inequality and living standards. This column investigates to what extent continued development and implementation of artificial intelligence across all industries will follow similar trends and expose certain job types to displacement and a fall in demand for human labour.

The method used to explore the impacts was first applied to historical cases such as industrial robotics and software. I established a correlation between the job types I identified as 'highly exposed' to these advancements and declines in employment and wage rates over the coinciding period. I then took the framework of this method and applied it make predictions of what job types are most 'highly exposed' to artificial intelligence. What I found was a contrast to the effect of robotics and software on wage inequality compared to artificial intelligence. Artificial intelligence is directed towards high-skilled tasks and job types that require higher forms of education. As a result, if historical patterns of substitution of human labour continues it can be assumed that wage inequality will actually be reduced as higher earning job types begin to suffer from a reductio in labour demand and wage rates.

Method

To analyse past impacts of technological advancement and predict future impacts I have developed a new method. I examined the overlap between the text of job task descriptions and the text of patents to construct a measure of the exposure of tasks to automation. To do this I document the tasks a given patent describes as being able to achieve and characterize the kinds of people that would be in these occupations. For example, age, gender, qualifications. I then study the correlation between exposure scores and changes to employment and wages. Those job types with highest exposure see the greatest decline in employment levels and wage rates. Applying this method to past events of technological change aforementioned yielded clear results. The characteristics of people in job types which robotics were patented to displace are clearly defined. Individuals with less than a high school education, in low-wage occupations were the most exposed. Men under 30 are the most exposed as the likely hood they are performing what is termed “muscle” tasks is greater than any other subset of the working population. The rate at which exposure falls as levels of education rise is quite sharp. Robotics can conduct simple, physically intensive tasks but are not capable of critical analysis or creativity.

However, there is significant evaluation of this methodology that needs to be made to fully understand the results discussed and the extent to which they are completely accurate. There are many ways in which development of innovative technology can affect wage demand in different industries both directly and indirectly. Changes in adjacent industries can affect cost and demand of a product, all of which affect labour demand and therefore wage rates which is an expression of current human labour demand. These kinds of changes are not accounted for or quantified in this method.

There are also inverse reactions that oppose the expected result that states high exposer will result in a fall in demand for human labour and wage rates. There are scenarios in which automation reduces cost of that occupations output. Therefore, the price level of output may fall and, depending on price elasticity of demand, cause a rise in demand so much so that the initial reduction of labour demand is offset or even experience a net growth to cope with demand. An example of this was argued by Bessen (2015), that ATMs, which automated some of the tasks of a bank teller, actually increased labour demand for this occupation by reducing total costs of opening a new branch. The result being bank teller per bank was reduced but total number of bank tellers increased as a sufficient number of new branches were opened.

Artificial Intelligence

The key takeaway from the article is that AI is qualitatively different from previous technological advancements that altered the landscape of the labour market in its entirety. The difference means that different occupations and job types will be affected and in separate ways.

I use the term artificial intelligence to refer to machine learning algorithms. Specifically, two kinds of machine learning algorithms: supervised learning and reinforcement learning algorithms. A supervised learning algorithm learns functions that map inputs into outputs from training data consisting of example input-output pairs. A reinforcement learning algorithm, by contrast, learns how to take actions in a dynamic environment in order to achieve an objective.

For artificial intelligence, a human programmer defines the learning algorithm, which then learns for itself through new data or experimentation on how to complete an objective. This is far more advanced than software which is confined to predetermined parameters of "if-then" steps which lead to an outcome.

Verb	Example nouns	Verb	Example nouns
recognize	pattern, image, speech, face, voice, automobile, emotion, gesture, disease	**determine**	state, similarity, relevance, importance, characteristic, strategy, risk
predict	quality, performance, fault, behavior, traffic, prognosis	**control**	process, emission, traffic, engine, robot, turbine, plant
detect	signal, abnormality, defect, object, fraud, event, spammer, human, cancer	**generate**	image, rating, lexicon, warning, description, recommendation
identify	object, type, damage, illegality, classification, relationship, importance	**classify**	data, object, image, pattern, signal, text, electrogram, speech, motion

Table 1 - Top Verbs and characteristic nouns used in AI patents.

Figure 1 shows the most frequently used verbs and nouns in AI patents. The types of verbs and nouns used are quite different from those that would be used for robotics and software job types, which suggests AI would and will affect different occupations now and in the future.

By employing the method discussed earlier and analysing overlap between job descriptions and patents of emerging AI I have identified the most exposed job types and occupations.

Most exposed occupations	Least exposed occupations
Clinical laboratory technicians	Animal caretakers, except farm
Chemical engineers	Food preparation workers
Optometrists	Mail carriers for postal service
Power plant operators	Subject instructors, college
Dispatchers	Art/entertainment performers

Table 2 - Occupations with highest and lowest exposure to artificial intelligence.

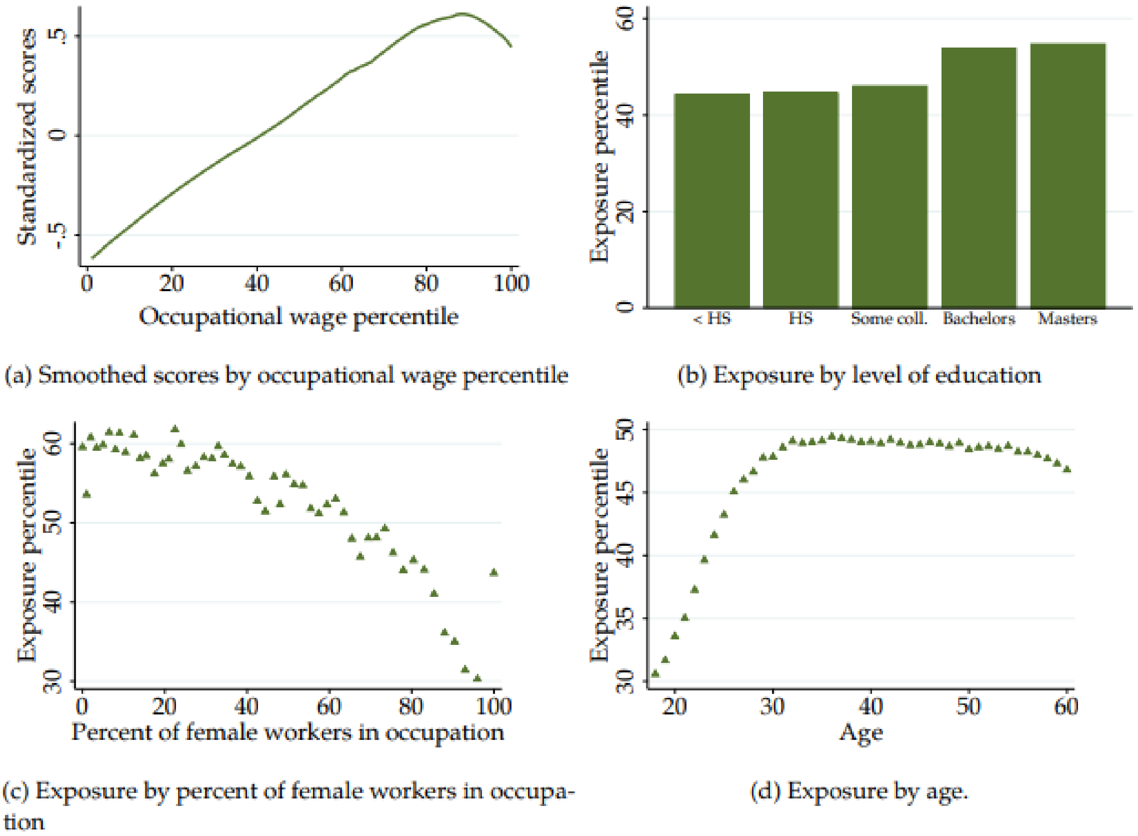
In figure 2 above, we can see some of the occupations most exposed to AI. It becomes clearer to understand why these job types and occupations are more at risk when you summarise the tasks at hand.

Clinical laboratory technicians perform the visual and analytical work of identifying pathologies from medical tests; AI applications have now been developed to automate much of this work (Janowczyk and Madabhushi 2016). Chemical engineers design and operate chemical production processes. AI algorithms are particularly well-suited to these discovery and optimization tasks and are already being used in such applications (Agrawal, McHale, and Oettl 2019; Goh, Hodas, and Vishnu 2017). And Optometrists detect diseases in the eye. Optometry is the area of medicine that has seen perhaps the most success of AI algorithm.

to date (De Fauw et al. 2018). These types of occupations are high-income jobs which is directly opposed to the results of displacement due to robotics and software.

Having identified the main job types and occupations which are most exposed to displacement by AI, we can also analyse how different demographics will be affected. This is based purely on descriptive evidence of the kinds of people and which traits they have for people who work occupations most exposed.

Figure 1 below, shows that in panel A, as occupation wage increases so does the exposure score all the way up to the 90th percentile. The consequences of this means we can make assumptions that due to AI; wage inequality will be reduced. This is in direct contrast to the effects robotics and software had on labour demand, wage rates and wage inequality. By higher income occupations being subject to displacement they face falling labour demand, wage rates and therefore wage disparity between 10th and 90th percentile. However, it should be noted that after the 90th percentile as we approach the 1%, exposure falls again which means here wage disparity actually has a likelihood to rise.



(a) Smoothed scores by occupational wage percentile

(b) Exposure by level of education

(c) Exposure by percent of female workers in occupation

(d) Exposure by age.

Figure 1- Exposure to AI by demographic group.

Panel B represents the change in levels of exposure based on increasing degrees of education. Those with the highest levels of education being the most exposed. Given the correlation between levels of education and average wage, we can conclude that this too demonstrates that high wage occupations are most at risk.

Conclusion

We are too early in the development of AI to know how far we will push the boundaries of the possibilities, and too early also to know how rapid the diffusion will be. AI could be faster to diffuse than previous technologies, given the lack of a need to manually specify its rules of operation and implementation of computing and associated hardware into everyday life.

However, the results leave little room for uncertainty that artificial intelligence will affect vastly different kinds of occupations, and so different kinds of workers, than software and robotics. It is high-skill occupations that are most exposed to artificial intelligence. Moreover, artificial intelligence is much more likely to affect highly educated and older workers than previous technologies which targeted low-income, low-skill occupations. As a result of this affect on labour demand in the future, AI could compress wages in the middle of the inequality distribution but expand inequality at the top.

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