Workforce Analytics

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Assignment 2: The Workforce of the Future

Group 4

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Introduction

The purpose of this report is to study and analyze the effects of Artificial Intelligence (AI) and automation in the workforce. More precisely, a thorough literature research was undertaken to define automation and understand its characteristics and, based on this study, an analysis on the O*NET dataset was performed in order to identify automation opportunities. Using this analysis, we tried to understand the changes this automation would bring to people's jobs, organizations and the economy as a whole and we compared our findings with the PriceWaterhouseCoopers "Workshop: Impact of AI on the UK labour market", 2019 report.

Chapter 1: Defining Automation

2.1 What are AI-related technologies useful for?

A major impact on society has already been noticed due to Artificial Intelligence, with significant changes on both, a human's daily life and an organization's typical function. While its positive influence in productivity and efficiency is widely accepted, there are also approaches that look deeper into the ethical part of this disrupting technology.

As with every technological revolution, some job may disappear while other opportunities will come further improving the quality of life (Singh, 2017). Cases include 'Disease Diagnosis and Medication' with personalized medicine based on DNA characteristics and even robots that remind ill people to take their medicine, 'Mental Health support' where algorithms can flag people who are at risk of self-harming, 'Mobility' with self-driving cars that increase safety and allow disabled citizens to move in the city, ‘Education’ with personalized classes based on students’ abilities and much more such as ‘Sports’, ‘Insurance’ etc (Forbes, 2019).

Moreover, economic growth is highly probable to be followed with the implementation of AI (Executive office of US President, 2016) on the long run. It is well known that technological progress is the main factor that affects GDP growth, comparing to capital and labor hours. As labor productivity increases, average salary increases as well, and hence workers are able to work less hours while affording more goods and services (including higher living standards and more leisure hours).

The implementation of AI can help businesses and organizations increase productivity by 40% or more, while boosting profitability by 38% (Accenture Newsroom, 2018). The benefits of Artificial Intelligence are highly correlated with ‘customer satisfaction’ allowing personalized customer support (even with the use of chatbots), ‘hiring process’ by exploiting this technology to make the whole process smoother and less costly, and ‘automated work’ meaning the automation of cognitive workflow which frees lots of precious working hours to employees.

2.2 How you identify opportunities to introduce automation?

The necessity for firms, employees, and governments to understand and measure possible opportunities or risks due to the even wider introduction of artificial intelligence applications, leads to establish a framework to determine whether a job can be automatized. The literature provides different examples and approaches to this question.

Overall, academics agree on the fact that the historical jumps in technological levels created jobs, in the long term, rather than destroy them (Arntz, Gregory & Zierahn, 2017). However, in the relatively recent case of artificial intelligence, some anxiety hit the academics; for instance, the book by Brynjolfsson and McAfee (2014) imagined a new kind of machines, that differ from the ones invented during the Industrial Revolution because able to perform cognitive operations and, potentially, substitute human work at all. Extreme views like the former have been mitigated by researches which investigated the role of different factors. For example, a pioneering book by Leicht and Fennell (2001), followed by Susskind (2015) and focused especially on professional jobs, depicted a transformation where advantages are evident, especially in terms of flexibility of companies’ organization. More recent works tried to describe possible frameworks where automation hits especially repetitive and routine jobs (Marcolin, Miroudot & Squicciarini, 2016). Even though that seems to be a valid explanation, these analysis lack of completeness to be effectively used to compute a measure. One of the first attempts to broadly evaluate how many jobs could be affected by the introduction of AI has been made by Frey and Osborne (2013). The percentage they reported was extremely high (47%) because jobs have been considered as an inseparable element. Following that, a more refined approach has been proposed later, by Arntz, Gregory and Zierahn (2017), where any single job has been split in a set of tasks. They argued that even though most of the jobs are composed by at least one task suitable to be disrupted by AI, the percentage of job expected to disappear because completely automatable, is significantly lower.

Many researchers have recognised in the tasks-based analysis a superior approach and, among the other, important contributions come from a pair of research reports published by McKinsey & Company during year 2017 (2017a, 2017b). The first one built a framework focused on 18 humans’ capabilities grouped in the following five areas: sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, physical capabilities. The results are quite fascinating because the state of art in terms of ability of machines to replicate human tasks is carefully described. For instance, physical capabilities are easily replaceable in terms of mobility, but not in terms of ability in manipulate object with sensitivity and dexterity. Building on this foundation, the second report provided examples of jobs unlikely to be disrupted by AI (care providers, professionals, technology professionals, builders, managers and executives, educators and "creatives”) in comparison with others more suitable to be replaced by machines (some customer interaction jobs, office support jobs). Nevertheless, the most relevant result is the attempt to define a general job taxonomy: jobs which are the most likely to be automated have the following features: less personal interactions, predictable or composed by repetitive tasks; on the other side, jobs who are the least likely to be automated have the following characteristics: needing of logical reasoning, implying social/creative skills or management-related.

<u>Chapter 2: Identifying Opportunities in O*NET Data</u>

3.1 Categorization of Jobs using Unsupervised Learning

3.1.1 Preprocessing

The raw O*NET data set contains paragraph descriptions of the tasks performed within the role from which the key tasks were extracted and assigned to a new variable. The transformed data set contained 974 observations with 923 unique tasks. In order to represent each task, we decided to use the first word for each task, which contained a verb that characterized this task.

Title	Task	Chaperone	Decorate	Sterilize	Sprinkle	Embalm	Apportion	Search	Convert	...	Flag	Contract	Plan	Refinish	Conceal	Perforate
Accountants	Develop Prepare Review Prepare Establish Analy...	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
Actors	Collaborate Portray Work Perform Study Learn A...	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
Actuaries	Ascertain Design Determine Provide Analyze Con...	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
Acupuncturists	Insert Maintain Adhere Identify Maintain Analy...	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
Acute Care Nurses	Perform Manage Document Diagnose Administer As...	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

Table 1: Categorical dataset containing jobs in rows and verbs in columns

Due to the curse of dimensionality, using all of these as features would result in poor model performance. As a result, it was decided that the optimal strategy would be to generate a new set of features.

Feature Set 1: Clustering Similar Tasks

The first set of features were generated by grouping similar tasks using word vectorization. To do this, the Word2vec library was employed to create word embeddings for each task which were then clustered using a K-means algorithm. To tune the hyperparameter, *K*, the silhouette score and inertia (elbow method) were plotted over a range of *K* values from two to eight as shown in Figure 1. Although both scores indicate an optimum value of three, the model performance may suffer from too few features and, hence, five was selected as the second-best option.

Figure 2: K-value tuning for feature clustering

Taking an in-depth look at the types of tasks within each of the five groupings, it was possible to assign labels of: 'managerial tasks', 'uncommon tasks', 'repetitive tasks', 'logical tasks' and 'mixed tasks'. Some examples of tasks within each labelled cluster are given below in Table 2.

Cluster	Sample Tasks
Managerial	Represent, Oversee, Promote
Uncommon	Irrigate, Transplant, Euthanize
Repetitive	Compute, Provide, Measure
Logical	Prepare, Assess, Negotiate
Mixed	Appraise, Sing, Walk, Steer

Table2: Sample tasks from each labelled cluster

Feature Set 2: Job Title Keywords

Whilst the clustering of tasks may implicitly separate job hierarchies, a more explicit approach was also undertaken utilizing the job titles. All job titles in the data set were separated by word and the top five most frequent keywords extracted to form a new set of categorical features. The top keywords were: 'machine', 'managers', 'teachers', 'technicians' and 'workers' where several hardcoded amendments were made to include jobs such as chief executives within the managerial grouping.

3.1.2 Modelling

Using the generated features and the Word2vec library, three models were built and then compared for performance, before selecting the most superior.

Model 1: K-means Clustering, Phrase Embedding

The first approach was somewhat experimental and involved embedding the task list for each job as a phrase, before clustering using K-means. Duplicates within the class list were kept adding weight towards those tasks. Since the task lists are not real phrases, it was expected that performance would be relatively low for this modelling approach, but it could be used as a benchmark for other models.

Model 2: K-means Clustering, Word Cluster Counts

This model utilized feature set 1, creating frequency counts for each time a task from a respective job appeared within each word cluster. These numerical features were then clustered using K-means. Table 3 shows a sample of jobs from the created data set.

	title	Mixed Tasks	Repetitive Tasks	Managerial Tasks	Logical Reasoning Tasks	Uncommon Tasks
0	Accountants	2	4	1	10	0
1	Actors	3	3	2	8	3
2	Actuaries	0	5	2	7	1
3	Acupuncturists	1	4	1	10	2
4	Acute Care Nurses	0	7	1	18	1

Table 3: Frequency counts for tasks with respect to task cluster

Model 3: Hierarchical Clustering, Categorical Features

The final model used both feature set 1 as binary variables: 1 if a task appeared in a word cluster, 0 otherwise. This was to form a categorical data set for which feature set 2, key title words, could be included. Table 4 shows a sample of jobs from the categorical data set.

	title	Mixed Tasks	Repetitive Tasks	Managerial Tasks	Logical Reasoning Tasks	Uncommon Tasks	Machine	Managers	Other	Teachers,	Technicians	Workers
0	Accountants	1	1	1	1	0	0	0	1	0	0	0
1	Actors	1	1	1	1	1	0	0	1	0	0	0
2	Actuaries	0	1	1	1	1	0	0	1	0	0	0
3	Acupuncturists	1	1	1	1	1	0	0	1	0	0	0
4	Acute Care Nurses	0	1	1	1	1	0	0	1	0	0	0

Table 4: Categorical features for word cluster and key job titles

3.1.3 Performance Analysis

Due to the inherent lack of a target variable within unsupervised learning, assessing performance can be difficult. For this application, however, whilst we wish to categorise jobs generally, a predominant focus of this report was to unveil similarities between jobs and tasks likely to be automated.

As a result, the chosen the performance metric we decided to use to compare the different models, was the proportion of jobs expected to be automated in the future across the four job groups. To do this, a binary variable (1 denoting automation prone, 0 not) was created by manually classifying each job against our automation definition cited in Chapter 1. Whilst methodology may not scale well, it can be considered a proof of concept for an approach which could later be coded. Approximately 45% of jobs were labelled as prone to automation, the balance of the two classes further endorsing it as a suitable metric.

The rationale for the approach was that the best model for our purpose would create clusters with highly disproportionate levels of automation prone jobs, thus effectively clustering by features correlated automation. It was found that whilst models 1 and 3 exhibited little to no segmentation of automation prone jobs, model 2 performed exceptionally; specifically, clusters 2 and 3 where ~78% and ~9% of jobs are prone to automation respectively. Thus, model 2, K-means on word cluster counts, was selected as the optimal model. Four clusters were found to give optimal performance across the three models, specifically Model 2, and this was kept constant across all three models for easier comparison.

Cluster	Model 1	Model 2	Model 3
1	0.422	0.674	0.416
2	0.492	0.088	0.351
3	0.367	0.781	0.417
4	0.507	0.287	0.541

Table 5: Model comparison: proportion of cluster prone to automation

3.1.4 Cluster Evaluation

Using model 1, we then decided to plot the distribution of the task clusters for each job class. We see on Figure 2 below that Job Class 2 which has a high proportion of its jobs prone to automation also has the highest proportion of repetitive tasks and the lowest proportion of logical reasoning tasks. Additionally, job class 1 which is the least prone to automation also has the highest proportion of logical reasoning tasks and the lowest proportion of repetitive tasks.

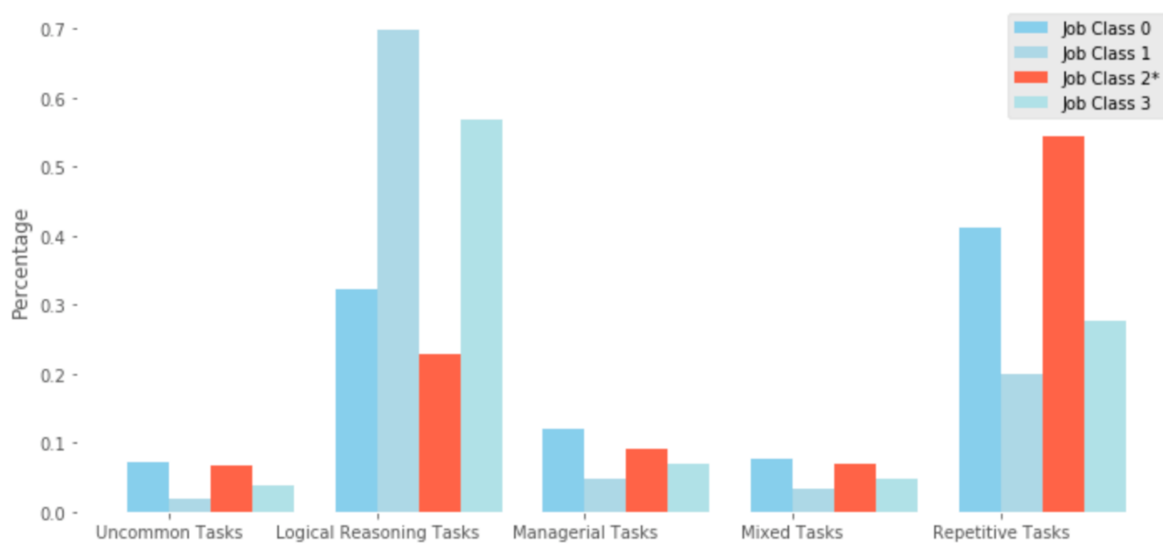

Figure 2: Task distribution by job cluster

Furthermore, we plotted the distribution of the task clusters across the 5 most recurrent job titles in the O*NET data set. We see that managers and teachers both have a high proportion of logical reasoning tasks and a low proportion of repetitive tasks while technicians and workers perform a high number of repetitive tasks and a lower average number of logical reasoning tasks than managers or teachers.

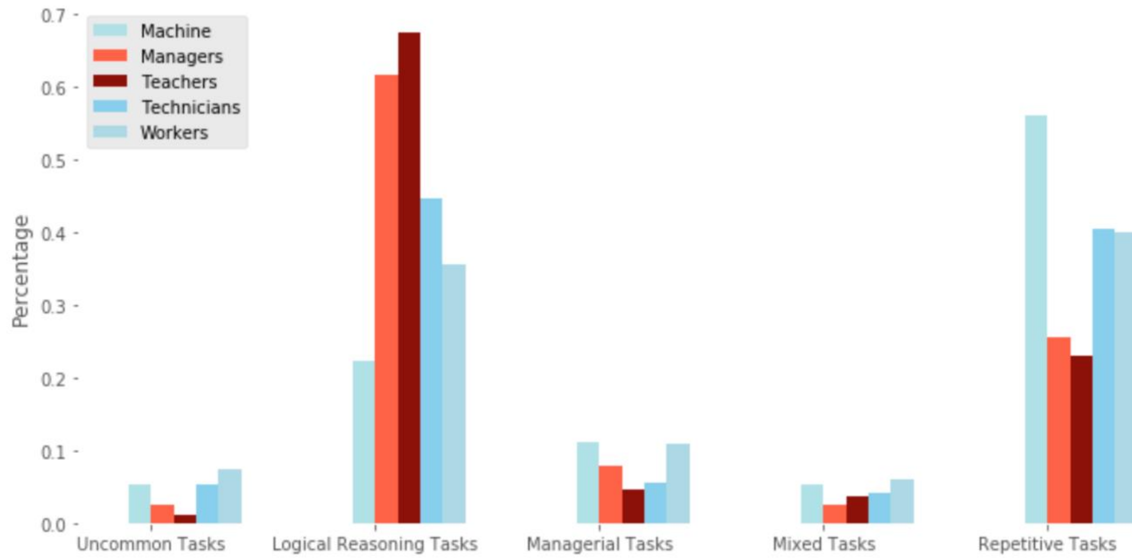

Figure 3: Task distribution by job title

The McKinsey report (McKinsey Global Institute, 2017b) outlines that jobs which are most likely to be automated share similar characteristics. Indeed, according to the report, these jobs require little personal and social interactions, have predictable or unpredictable physical activities and mostly consist of repetitive tasks. On the other hand, jobs which are least likely to be automated require logical reasoning, social or creative skills which are often skills that managers need. It is important to note that the clusters of tasks we identified reflect these characteristics and thus, our categorization analysis enabled us to identify the professions which are prone to automation such as technicians, and least prone to automation (managers and teachers).

3.2 Consequences of AI automation

3.2.1 Consequences of AI on jobs

Prediction machines are going to replace tasks that are predictive or can be implemented using a prediction mechanism. From an economic point of view, the wide use of AI technologies and the cheaper exploitation of prediction machines will result in increasing the value of other actions related to a human task which are complement to prediction, such as judgment and feedback learning *(Agrawal et al, 2018).* Consequently, jobs with tasks whose main value is predicting will be devalued, whereas those whose main value is to use judgement will become higher in demand. This explains for example why we identified technicians as a job prone to automation and managers and teachers less probable to be replaced.

3.2.2 Consequences of AI on organizations

Another complementary feature of prediction is the data used as an input to train the models. This means that data will become a valuable resource in the new era of AI, with organizations investing heavily on the acquisition and maintenance of datasets required for their prediction machines *(Shrikanth, 2018)*. For example, Waze is a company which predicts the best route for its users. But, in order to generate this valuable data, it has partly sacrificed customer experience by sending some users into traffic *(Harvard Business School Digital Innovation and Transformation 2015)*.

However, this strong need for data can easily conflict with privacy issues and, hence, an ethical framework on the use of this technology needs to be formed so that organizations keep respecting individual rights and privacy issues *(Floridi and Cowls, 2019).*

This widespread use of AI tools and the high precision of prediction machines may also help organizations change their business strategy *(Namaki, 2019)*. A real-life example is based on Amazon's patent for anticipatory package shipping *(United States Patent, 2013)*, which could lead to a potential change of Amazon's strategy from a shopping-shipping company to shipping-shopping company *(Agrawal et al, 2017)*.

However, the culture of the organization should also be aligned to the strategy, so that the implementation of the change can be successful *(Grousberg, 2018)*. Firms should encourage interdisciplinary collaboration through the creation of small with a mix of skills and perspectives on any given task. This cross-functional structure could strengthen the judgement part of any given task and result in a better usage of the prediction tools. In addition, companies should change their organizational structure to accommodate a test-and-learn process. This means companies need to follow a less hierarchical structures which can extract results faster without strict evaluation from top managers, which reinforces the learning part of the human tasks. Moreover, organizations need to aim to educate everyone in this new era of technology and offer incentives through training programs to their employees to understand the value of AI and adopt it effectively in their everyday tasks *(Fountaine et al, 2019)*.

3.2.3 Consequences of AI on economy

At an even higher level, the disruption of AI will influence wages and economic distribution. Although it is widely accepted that automation will result in rise of productivity and economic growth, it is also likely that it will create a wage polarization and reinforce income inequality by pushing down wages of mid-skilled workers *(Korinek, 2017).* There are also concerns that the shifting of national income away from labour may lead to the concentration of wealth to the big tech companies and exacerbate present income inequalities. In addition, as with other industry revolutions, it is expected that on the long run more jobs will be created, but on the short-term unemployment will rise, demanding government policies which support the training of people to the new AI era but also protect labour rights *(PricewaterhouseCoopers, 2018)*.

Chapter 3: Findings Comparison with PwC Report

After completing our AI algorithm analysis, we saw that we have several word clusters. In the first of our clusters, we identified jobs that require logical reasoning tasks, in the second jobs that involve repetitive tasks and in the third those that involve managerial tasks. We also split our words in other clusters, but those three were the ones that we identified as most important to mention.

Moreover, we also clustered our previously mentioned word clusters based on job title. We observed that the job titles that include the words "Machine", "Managers", "Teachers", "Technicians" and "Workers" were the most frequent ones. What we managed to do with such a classification, was to prove that, for example, managers and teachers belong to more logical reasoning tasks. Working in a similar way for all our most frequent job titles, we classified them as including either repetitive or logical reasoning tasks. Thus, we concluded that jobs related to a machine, which involve repetitive tasks are more likely to be automated, whereas those of managers or teachers that involved more logical reasoning and social interaction are unlikely to be automated.

As for the comparison of our findings with PwC's analysis (PricewaterhouseCoopers, 2018), we can see that we agree on which occupations are unlikely to be replaced by AI technologies. Job positions that include management, meetings, events or negotiations are considered by both reports as non-automatable. However, our team added some extra value to that research, since we didn't form our clusters based on just asking people as we see in the PwC's analysis, but using machine learning algorithms as previously presented in the given report. Finally, another differentiation is that we managed to cluster our words, not only based on jobs, but also based on the tasks of each job, and thus provide more accurate results.

Conclusion

The necessity for companies to understand possible opportunities due to the arrival of artificial intelligence, raised the controversy of whether a job can be automated or not. Based on our analysis and on the McKinsey report (McKinsey Global Institute, 2017b), we concluded that jobs with repetitive tasks are more likely to be automated, whilst those requiring logical reasoning are unlikely to. However, whereas for roles such that of machine user and teacher we have a clear trend for automation or not, for others such that of workers or technicians we need to focus more on the tasks than on the job title. It is certain though that the progress of AI will push people and organizations to widely adopt the new prediction tools and put emphasis on judgement rather than predictions in order to fully exploit this new opportunity and remain competitive in the new environment.

References

Smith A. & Anderson J. (2018). AI, Robotics, and the Future of Jobs
Available from: http://www.fusbp.com/wp-content/uploads/2010/07/AI-and-Robotics-Impact-on-Future-Pew-Survey.pdf

Forbes, 2019: https://www.forbes.com/sites/quora/2019/08/20/how-can-we-use-artificial-intelligence-to-improve-society/#165f741395e8

The President, E. O. 2016. "Artificial intelligence, automation, and the economy." Technical report, Executive Office of the US President.

Accenture Report: Artificial Intelligence Has Potential to Increase Corporate Profitability in 16 Industries by an Average of 38 Percent by 2035 (Accenture Newsroom, 2017)

Arntz M., Gregory T. & Zierahn U. (2017) Revisiting the risk of automation. Economic Letters. Available from: https://doi.org/10.1016/j.econlet.2017.07.001.

Brynjolfsson E. & McAfee A. (2014) The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. London, WW Norton & Company;.

Diaz Lopez J. A., Molina-Solana M. & Kennedy M. T. (2018) foo.castr: visualising the future AI workforce. Big Data Analytics. Available from: https://doi.org/10.1186/s41044-018-0034-z.

Frey C.B. & Osborne M.A. (2017) The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change. Available from: https://doi.org/10.1016/j.techfore.2016.08.019.

Leicht K. T., Fennell M. L. & Freidson E. (2003) Professional work, a sociological approach. Canadian Journal of Sociology. Vol. 28, Iss. 1.

Marcolin, L., S. Miroudot & M. Squicciarini (2016), Routine Jobs, Employment and Technological Innovation in Global Value Chains. OECD Science, Technology and Industry Working Papers, No. 2016/01, OECD Publishing.

McKinsey Global Institute (2017) A future that works. Automation, employment and productivity. McKinsey & Company.

McKinsey Global Institute (2017) Jobs lost, jobs gained: workforce transition in a time of automation. McKinsey & Company.

Moretti E. (2013) The new geography of jobs. Boston, MarinerBooks.

Susskind R. & Daniel Susskind (2015) The future of the professions: How technology will transform the work of human experts. Oxford, Oxford University Press.

Agrawal, A., Goldfarb, Avi, author & Gans, Joshua, author, 2018. Prediction machines : the simple economics of artificial intelligence.

G., S. (2018) 'Data Is The New Oil', Dataquest, 36(9), pp. 8–11.

Floridi, L., & Cowls, J. (2019). A Unified Framework of Five Principles for AI in Society. Harvard Data Science Review, 1(1). https://doi.org/10.1162/99608f92.8cd550d1

Jain, P., Gyanchandani, M. & Khare, N., 2016. Big data privacy: a technological perspective and review. Journal of Big Data, 3(1), pp.1–25.

Namaki, M. S. S. E. (2018) 'How Companies are Applying AI to the Business Strategy Formulation', Scholedge International Journal of Business Policy & Governance, 5(8), pp. 77–82.

Spiegel, J. et al. (2013) 'Method and system for anticipatory package shipping', US 8.615.473 B2

Agrawal, A., Gans, J. and Goldfarb, A. (2017) 'How AI Will Change Strategy: A Thought Experiment', Harvard Business Review Digital Articles, pp. 2–5.

GROYSBERG, B. et al. (2018) 'The Leader's Guide to Corporate Culture. (cover story)', Harvard Business Review, 96(1), pp. 44–52.

Fountaine, T., McCarthy, B. and Saleh, T. (2019) ‘Building the AI-Powered Organization. (cover story)’, Harvard Business Review, 97(4), pp. 62–73.

Korinek, A., 2017. Artificial Intelligence and Its Implications for Income Distribution and Unemployment.

PricewaterhouseCoopers, (2018), The macroeconomic impacts of artificial intelligence.