# More than a machine: An analysis on the susceptibility of jobs to automation

RP524

## Abstract

Advances in computing through the advent of machine learning and artificial intelligence, as well as advances in robotics has led to a surge of debate on what jobs will be automated by machines in the future, and to what degree. The threat posed by automation to worldwide employment is significant, with industry titans like Elon Musk explaining “this is going to be a massive social challenge. There will be fewer and fewer jobs that a robot cannot do better” (Larson). The purpose of this paper is to provide a quantitative analysis of what features of a job can be computerized, and extrapolating these results to pinpointing the types of jobs that are most likely to be automated in the future. The bulk of our data was derived from the O*NET database from the U.S. Department of Labor which provides information to the skills required for different occupations. We used these statistics and broke them down into three main variables, original reasoning, social and physical manipulation, and creativity. We then developed an equation using a hyperbolic tangent function to simulate a reverse S-curve, taking into account these three main variables and including how the probability of automation increases over time. Using a statistical regression line, 98.28% of the variation of 2013’s Frey and Osborne’s job automation analysis is accounted for by our model. An analysis our calculated probabilities concludes that jobs requiring a high level of novel & creative thinking, high levels of physical flexibility and mobility, or a large amounts of interpersonal interactions are unlikely to be replaced by artificial systems. Conversely, predictable jobs involving repetition of similar tasks, little to no mobility, and minimal social interaction have a significant chance of being automated in the future.

## Background Literature Review

The advent of new inventions replacing the old has great potential to disrupt the existing social order. During the Industrial Revolution, the effect of these new inventions were profound. The role of humans in the workforce changed as "human beings were no longer wanted as a source of mere indiscriminate power. What could be done mechanically by a human could be done faster and better by a machine. The human being was needed now only where choice and intelligence had to be exercised" (Wells 367). The Industrial Revolution did not solely take away jobs, but it redefined the roles that humans had to undertake, making new jobs intertwined with mechanical inventions.

With machines reducing the need for a wide range of skills required of workers, instead opting for specialized skills required for each machine, employers are enabled to increase their division of labor. This means that workers have to undertake less distinct actions, rather having different groups of workers each accomplishing specific tasks (Robertson and Lee 331). Consequently, the reduced amount of skills required of each worker makes it easier for these workers to be replaced. The Industrial Revolution helped employers in two ways, increasing productivity for each individual worker with fewer, but more specialized skills, and a reduction in bargaining power for each worker due to fewer skills, allowing employers to lower wages (Robertson and Lee 331-332).

These technological changes illustrated during the Industrial Revolution exemplify the principle of creative destruction put forward by Schumpeter. Creative destruction, as Schumpeter describes, is a process with which innovation brings about restructurings in the economic system (Hospers 23). The rapid pace of change in innovation proceeding today creates a similar scenario in the labor force, with computerized automation having the potential to drastically remake our economic systems today.

The capabilities of automation are far more extensive than that of the new machines brought about during the Industrial Revolution. These aforementioned capabilities can be broken into the broad categories of language, reasoning, vision, and movement (Elliott 30).

Language capabilities of automated systems "have advanced beyond the challenges of typical language use at the word or sentence level, but they fall far short of typical extended language use at the lecture or book level" (Elliott 31). These language capabilities encompass skills of speaking, writing, reading, and understanding human speech and interpreting speech accurately. Symantec's Clearwell system is a solid example of language capabilities, as the system has been shown to analyze and sort 570,000 legal documents in two days, and successful identified the general concepts in each document (Frey and Osborne 17). Earlier language systems mainly focused on understanding language within a single topic area, but since then language systems have broadened their reach to a much greater range of topics (Elliott 31).

Reasoning capabilities of systems revolve around the ability to solve problems based on either existing data, or extrapolating results from past conclusions to novel situations. A major weakness of the reasoning capabilities of automated systems are due to the system being limited to the scope of the program with which it is written in. Although systems have been shown to have high levels of performance to tasks they are purpose built for, such as expertly analyzing geological landform data, these systems cannot be applied for different tasks and show only a narrow area of reasoning (Elliott 31). Another limitation of automated systems is that even when performing one task, if it finds itself in an unexpected situation that is outside the limitations of its programming, it enters an error state (Rus 5). The reasoning of these automated systems are exceptionally strong for a single task, but falls short in applying their skills to multiple tasks or indicating the flexible reasoning that humans have.

Automated systems have much to offer with regards to their visual and sensing capabilities. The utility of computers for CCTV (closed-circuit TV) operators is most apparent as computers' algorithms stay constant and provide an objective view of security camera footage as well as not having human lapses of concentration especially during after hours (Frey and Osborne 17). There has been much progress with visual systems as well, for instance the robot Baxter memorizes the patterns it experiences as a human worker guides the robot through the motions required for the task (Frey and Osborne 21). However, automated systems' weakness is an over reliance on low-level data to make conclusions and a lack of recognition of tying things together. This makes it hard for machines to determine if it has been in a specific place before or happen to be in a place with similar objects but a completely different environment (Rus 4). In summary, automated systems are good at picking up each individual detail in the environment, but has the most trouble tying these details together.

Movement capabilities within the context of automated systems encompasses "spatial orientation, coordination, movement control, and body equilibrium" (Elliott 32). Mobility for these systems depends to a large extent to the environment the system is in. Irregular and cluttered spaces are much harder for machines to navigate compared to well ordered warehouses such as the ones owned by Amazon using bar-code stickers on the floor to help guide the machines to their destinations (Frey and Osborne 25). The importance of mobility for these machines is most apparent for machines purpose built for disaster situations where it may be unsafe or impossible for humans to carry out the same task. Use of these disaster machines is apparent for cleaning up the Fukushima nuclear plant where different types of robots were used "Remote-controlled front-end loaders, backhoes, and other heavy equipment were put to work breaking up radioactive debris and loading it onto remote-controlled dump trucks. A four-legged walking robot investigated the reactor buildings… Swimming robots inspected pools… " (Beiser).

## Research Methodology

### Chosen Jobs

Financial analyst, Civil Engineer, Psychiatrist, Accountant, Office Clerk, Teacher, Cashier, Registered Nurses, Computer Systems Administrators, Firefighters

The jobs we decided were chosen randomly, making sure there was a wide base of different skills involved for each job. Using the US Department of Labor database O*Net OnLine to find relevant skills involved for each job, we combined these skills into three major categories. Jobs lacking skills in original reasoning, social and physical manipulation, or creativity are much more likely to be automated than jobs requiring one or more of these skills.

### Model

The adoption of a new technology has followed an ever-steeper "S-curve" found in logistic growth (Hall and Khan 2). To model the spread of automation, we assumed increasing automation to be akin to a new technology, allowing us to base assumptions off of logistic growth. Our model would take in three inputs ($R$, $M$, $C$, all decimal values between 0 and 1 exclusive that are indicative of level of given variable) found by grouping characteristics of a job that a given profession requires:

- **Original Reasoning (*R*)** is the ability to make connections and insights independently between separate sources of information to solve a problem. This includes the ability analyze information to draw insights not readily apparent.
- **Social and Physical Manipulation (*M*)** encompasses two ideas. First, the amount of face-to-face and emotional interaction required with other humans, and second, the level of precision in limb movement required to complete non-repetitive tasks (for example, this would be very high for a brain surgeon, but also for a vocal performer).
- **Creativity (*C*)** is the creation of new ideas, behaviors, and insights not directed under a precise task. For example, singers and songwriters would require high amounts of creativity in their profession.

Values for these three variables were estimated to the nearest tenth by reading the quantitative skill requirements (whole numbers from 0 to 100) for various professions under O*Net database. We got at the exact values for *C, M,* and *R* by first reading all the skill requirement ratings for all professions, and then estimating the total levels for a variable's related O*Net entries compared to other professions. Though this process is not perfectly quantitative, it was necessary to somehow consolidate O*Net's qualitative and quantitative data on job descriptions into a few manageable variables with the resource constraints for our report.

After the data were collected for all 10 randomly-selected professions, we designed an equation to model the likelihood of a profession being automated (defined as humans only being required to supervise computerized and/or mechanized tasks for a given job, and this phenomenon being widespread to over half the industry) in the US within the next century. For all jobs we analyze, we set any current level of automation to be the base level (zero) to analyze changes from. Next, our model is to output a low likelihood of automation if any one of *C, R,* or *M* are high and the rest are low. We based our model initially on multiplying probabilities for the three variables together, and later added logarithmic transformation for each variable to simulate the impact of having a high value for one variable resulting in a low automation likelihood. We then applied a hyperbolic tangent transformation to simulate an S-curve style of adoption where initial adoption is rapid (where the largest firms with the most resources and opportunity would automate tasks as soon as possible) after a period of research and development (*p*) but becomes more gradual as time progresses (a trickling-down effect). For *p*'s value, we chose 10. This serves as a brief buffering period - the short foreseeable future (of around five years) where the level of automation for selected professions would not change much from current levels.

$$P_A = \tanh[-10(\log R * \log M * \log C)] \quad \text{(our model)}$$

**Findings**

Figure 1 below shows the probabilities of automation for ten randomly selected jobs. These results mostly follow what is expected of the jobs below. For example, accountants are widely expected to undergo significant automation in the future (Dhar), and our model predicts almost a 90% probability for automation within the next century. As expected, the jobs requiring high levels of intrapersonal skills, creativity, and thought are not likely to be automated in the next century (Sumagaysay). Compared to previous research done in this subject by Carl Frey and Michael Osborne in 2013, the likelihood of automation for the given jobs using our model follows the same general trend, where professions needing high levels of any of original reasoning, social and physical manipulation, and creativity are not likely to be automated. Figure 2 compares the findings from our model to Frey and Osborne's 2013 model.

| Job | Original Reasoning ($R$) | Social and Physical Manipulation ($M$) | Creativity ($C$) | Probability of Automation ($P_A$) |
|---|---|---|---|---|
| Financial Analyst | 0.8 | 0.4 | 0.6 | 0.0853 |
| Civil Engineer | 0.8 | 0.6 | 0.6 | 0.0477 |
| Psychiatrist | 0.7 | 1.0 | 0.8 | 0 |
| Accountant | 0.2 | 0.4 | 0.3 | 0.8966 |
| Office Clerk | 0.1 | 0.3 | 0.2 | 0.9987 |
| Preschool Teacher | 0.3 | 0.9 | 0.7 | 0.0370 |
| Cashier | 0.1 | 0.6 | 0.1 | 0.9766 |
| Registered Nurses | 0.6 | 0.9 | 0.6 | 0.0225 |
| Computer Systems Administrators | 0.8 | 0.6 | 0.4 | 0.0853 |
| Firefighters | 0.5 | 0.8 | 0.3 | 0.1514 |

Figure 1. Calculated variables for each job based on the O*NET Database, as well as probability of the job being automated in the next century based on our model.

| Job | Probability of Automation ($P_A$) | Frey and Osborne Model |
|---|---|---|
| Financial Analyst | 0.0853 | 0.23 |
| Civil Engineer | 0.0477 | 0.019 |
| Psychiatrist | 0 | 0.012 |
| Accountant | 0.8966 | 0.94 |
| Office Clerk | 0.9987 | 0.96 |
| Preschool Teacher | 0.0370 | 0.0074 |
| Cashier | 0.9766 | 0.97 |
| Registered Nurses | 0.0225 | 0.009 |
| Computer Systems Administrators | 0.0853 | 0.03 |
| Firefighters | 0.1514 | 0.17 |

Figure 2. Calculated probabilities of automation based on our model versus 2013 Frey and Osborne model.

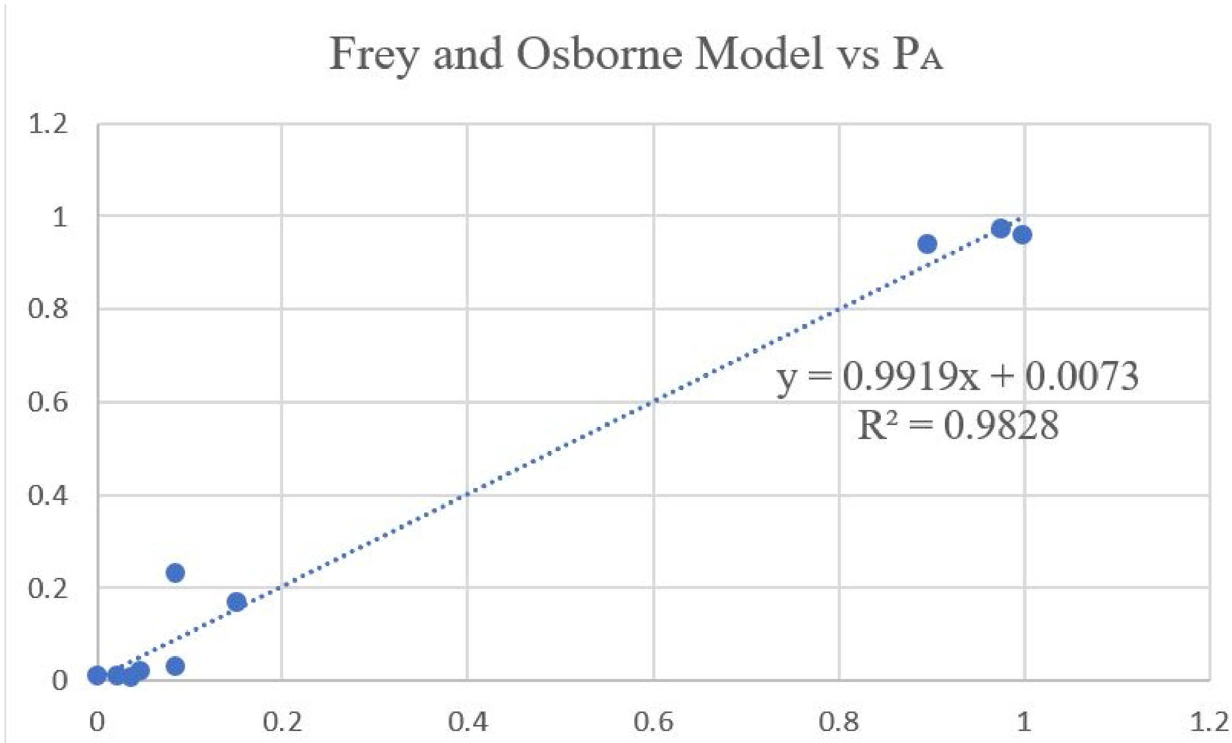


Figure 3. Regression line for calculated probabilities of automation versus 2013 Frey and Osborne model. 98.28% of our data's variation is accounted for by Frey and Osborne's model with 1.72% left in the residuals.

**<u>Conclusion</u>**

Our model found that jobs which require high levels of intrapersonal communication, creativity, and/or original thinking are unlikely to be automated in the next century. The jobs most at risk of automation are repetitive professions with low requirements for all three aforementioned tasks (for example, cashiers are at very high risk of automation). The history of automation from the industrial revolution onwards teaches a similar lesson as our model - that the professions that survive the threat of automation require complex thinking found only in humans.

But after discussing the findings of our model, we must address its drawbacks. There are quite a few shortcomings for this model. Our model rests on delicate assumption of technological adoption following logistic growth patterns found in history. We only addressed any governmental or societal resistance to automation with a short universal buffering period. We also relied on data for jobs in the United States through the O*Net database; our model is not applicable worldwide. Our model also relied a fair bit on our judgements of O*Net qualitative and quantitative descriptions for various professions in order to get decimal values for three variables. This approach attracts problems with replicability, but we relied the most we could on O*Net's quantitative descriptors for skill levels for various jobs in order to make the process of getting $R$, $M$, and $C$ values as replicable as possible.

Though our model may have a number of shortcomings limited by resources available to us, research into automation's impact on labor markets remains critical. Society will face several challenges as automation becomes more widespread. The two biggest concerns are short-run structural unemployment shocks and rising economic inequality. When automation arrives in an industry, a worker's skill set is no longer useful to his firm. When this happens for tens of thousands of jobs, "new work" cannot arrive fast enough to compensate for the sudden unemployment workers face. Entire professions like trucking can be wiped out over the course of a year with the arrival of self-driving cars, and the negative externalities associated with unemployment such as deteriorating health can risk harming large swaths of society (Litan). Secondly, increasing automation will lead to higher economic inequality. Most of the professions being automated will be low-skilled ones, and this will put downward pressure on the demand for low wage employees. Depending on the concentration of bargaining power in a labor market, the gains from automation (increased efficiency) may not necessarily trickle down to increased wages for workers (Autor).

But automation by no means is a net negative. Similar to trade, it's one of the inevitable processes of creative destruction that free up an economy's resources for more efficient prospects. Prior to the industrial revolution, more than nine in ten workers were employed in agriculture. That number has falled in under one in twenty for the present day. We don't experience extensive unemployment from the loss of agricultural jobs today because automation has a crucial positive benefits to an economy (Litan). It makes existing industries more efficient by making automated industries' intermediate outputs more productive. It creates demand for new jobs and goods, reinvigorating the labor markets. Lastly, automation works to reallocate resources and workers to more productive tasks so that an economy can expand its production possibilities. Automation is a key process through which we have experienced economic growth. Though it shouldn't (and possibly can't) be prevented, its impact should be continually researched to ensure a smooth transition to the future.

**Works Cited**

Autor, David. *Polanyi's paradox and the shape of employment growth*. Vol. 20485. Cambridge, MA: National Bureau of Economic Research, 2014.

Beiser, Vince. “The Robot Assault on Fukushima.” *Wired*, vol. 26, no. 5, May 2018, p. 68. EBSCOhost.

Dhar, Vasant. “Robots Will Soon Do Your Taxes. Bye-Bye, Accounting Jobs.” *Wired*, Condé Nast, 3 June 2017.

Elliott, Stuart W. “Anticipating a Luddite Revival.” Issues in Science & Technology, vol. 30, no. 3, Spring 2014, pp. 27–36. EBSCOhost.

Frey, Carl Benedikt, and Michael A. Osborne. “The Future of Employment: How Susceptible Are Jobs to Computerisation?” Technological Forecasting and Social Change, vol. 114, 17 Sept. 2017, pp. 1–72., doi:10.1016/j.techfore.2016.08.019.

Hall, Bronwyn H., and Beethika Khan. *Adoption of new technology*. No. w9730. National bureau of economic research, 2003.

Hospers, Gert-Jan. “Joseph Schumpeter and His Legacy in Innovation Studies.” Knowledge, Technology & Policy, vol. 18, no. 3, Fall 2005, pp. 20–37. EBSCOhost.

Larson, Quincy. “A Warning from Bill Gates, Elon Musk, and Stephen Hawking.” FreeCodeCamp.org, FreeCodeCamp.org, 18 Feb. 2017, medium.freecodecamp.org/bill-gates-and-elon-musk-just-warned-us-about-the-one-thing-politicians-are-too-scared-to-talk-8db9815fd398.

Litan, Robert E. “How to Adjust to Automation.” *Brookings*, The Brookings Institution, 13 Dec. 2018.

Robertson, Paul L., and Lee J. Alston. “Technological Choice and the Organization of Work in Capitalist Firms.” Economic History Review, vol. 45, no. 2, May 1992, pp. 330–349. EBSCOhost.

Rus, Daniela. “The Robots Are Coming.. (Cover Story).” Foreign Affairs, vol. 94, no. 4, July 2015, pp. 2–6. EBSCOhost.

Sumagaysay, Levi. “World Bank: Robots Are Taking Some Jobs, but Not All.” *The Mercury News*, Digital First Media, 3 Jan. 2019.

United States, Department of Labor, Employment & Training Administration. “O*NET OnLine.” *Occupation Search*, 4 December 2018, https://www.onetonline.org.

Wells, H. G. Short History of the World, Public Domain, 1922, pp. 365–369. EBSCOhost.