

Up to the Task

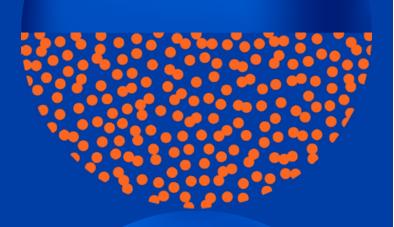
Toward a pathways model for enabling Canada's workforce transition

AUGUST 2018



Table of Contents

Executive Summary	3
Technology and the Changing Nature of Work	4
The history of technology and work	4
Technology and work today	5
The future of technology and work	6
Related Studies	7
Need for Employment Pathways	10
Pathways Approach	11
Employment pathways defined	11
Methodology	11
Data	12
Examples	13
Conclusion and Next Steps	15
References	16-17





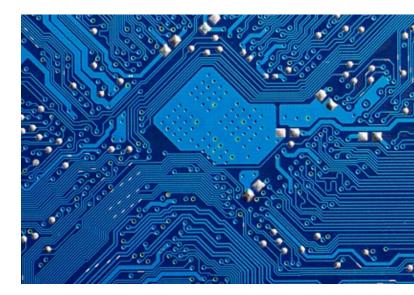
Executive Summary

Throughout history, new technologies have disrupted the workforce by automating tasks traditionally performed by humans. Now, at the dawn of the Fourth Industrial Revolution, the convergence of many technologies with digitization and artificial intelligence is expected to accelerate automation. As such, jobs that consist largely of automatable tasks are at risk of augmentation, and workers who are trained primarily in skills that complement these tasks are at risk of being displaced.

The mass automation of certain tasks creates the need for a coordinated effort to promote the development of skills that complement emerging technologies. Workers, employers, employment agencies, governments and educational institutions must all be involved. The World Economic Forum has called for a pathways approach to define how workers can make informed decisions about education and training in the context of automation and successfully transition between jobs. With the support of Google.org, MaRS is answering this call to action by creating the Employment Pathway Platform, a skills-based career guidance tool for the Canadian workforce. In this report, we present our methodology and example pathways to illustrate how they enable a user-friendly platform that is relevant for all stakeholders.

Our employment pathways map at-risk jobs to more sustainable career options based on inputs from key partners and data sources. For our example pathways, we use jobs from the Standard Occupational Classification (SOC) system, job characteristics from the Occupational Information Network (O*NET) taxonomy and data from the 2016 Canadian Census to identify three priority at-risk occupations for the working age population in Ontario. We partner with Faethm.ai, whose analytics platform determines the risk of automation for each job in our data set and matches at-risk jobs to more sustainable jobs based on shared attributes. We then map feasible job transitions, which we present as interactive visualizations of our pathways.

In the coming year, we will conduct additional research to uncover the needs of different regions and demographics as we build out a robust model for skills-based employment pathways. We will scale the Employment Pathway Platform and combine our pathways with actionable insights in order to enable the type of skills development that will help bolster the resilience of the Canadian workforce.





Technology and the Changing Nature of Work

The history of technology and work

Over the past two centuries, technological progress has helped to lift people out of squalor and poverty, raise the standard of living and improve overall wellbeing. Technological change can also be disruptive, rendering certain tasks and skills obsolete, unsettling economic structures, and contributing to unemployment and economic uncertainty.

Technological change has been the hallmark of economic progress throughout human history. Most notably, the onset of the first Industrial Revolution at the end of the 18th century put humanity on a path of economic development unprecedented in human history. Figure 1 outlines the evolution of technological progress since the invention of the steam engine, which was a key technological innovation of the First Industrial Revolution.

The Second Industrial Revolution introduced electric power in factories and the implementation of production lines. These inventions enabled the mass production of goods, lowering prices and making products more affordable for a wider range of people. The 1960s brought the Third Industrial Revolution, marked by the start of digitization and the broader application of computers in the workplace.

The current phase of technological change, often referred to as Industry 4.0, is characterized by machine-to-machine communication, artificial intelligence and the Internet of Things (Schwab 2016).

The Evolution of Technological Progress

Technological progress leads to higher levels of productivity. The diffusion of technology has occured at a faster pace in every subsequent Industrial Revolution since 1760.

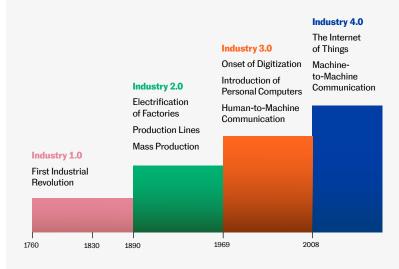


FIGURE 1:

The Evolution of Technological Progress since the First Industrial Revolution.

Technology and work today

The conventional view is that technological progress and innovation are desirable as they improve productivity, which in turn translates into higher incomes (Miller and Atkinson 2013). However, the most recent developments in automation, characterized by machine-to-machine communication and increased digitization, have a number of economists worried. In their view, the digital era could herald a time in which technology destroys old jobs at a faster pace than new ones are created (Krugman 2013, Sirkin et al. 2011, Levy and Murnane 2004).

Three main factors lead to this assumption (Brynjolfsson and McAfee 2014). First, due to Moore's law¹, technological progress can occur at an increased pace as processing capability decreases in cost. Second, today's technology is mainly of a digital nature, making it more pervasive and applicable in a variety of industries and occupations. Finally, information and communications technology enables new ways of combining and recombining ideas, and thus also enables the ability to spawn new innovations (Arthur 2011).

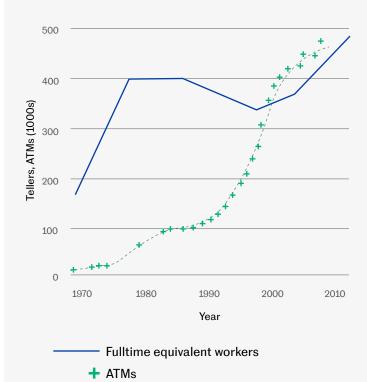
Combined, these factors result in the increasingly fast development of new technologies, and in the application of autonomous technologies to new disciplines and tasks. As Cowen (2013) puts it, "Increasingly, machines are providing not only the brawn but the brains, too." The pervasion of technology into new domains results in uncertainty about what occupations may change (or possibly not exist) in the future, what jobs will be augmented, and what new jobs may be created. Brynjolfsson and McAfee (2014) warn that the exponential progress in technical innovation could lead to an "inflection point" where societies will experience a net destruction of jobs.

Meanwhile, labour market data appears to contradict any apocalyptic forecasts. Between 2010 and 2016, for example, the manufacturing sector in the United States deployed 137,000 industrial robots; yet, during the same time period, manufacturing employment actually increased by around 890,000 jobs and the overall unemployment rate dropped by 5%.

This phenomenon is not new. As Bessen (2016) points out, when automated teller machines (ATMs) became widely adopted by financial institutions, the number of full-time equivalent bank tellers actually increased. The adoption of ATMs reduced the cost of running branches, as fewer tellers were needed. This savings enabled the banks to open more branches to better serve their customers, which more than made up for the bank tellers' initial job losses (see Figure 2).

FIGURE 2:

The Impact of Automation on Bank Tellers. Source: Bessen (2016).



The distinction between complete and partial automation is critically important with respect to labour market outcomes. When an occupation is completely automated, workers are replaced, resulting in overall job loss. However, when an occupation is only augmented (or partially automated), employment can actually increase.

For example, Bessen (2015) shows that during the first Industrial Revolution around 98% of the human labour in cloth weaving became automated, yet the total number of weaving jobs actually increased. In effect, automation increased productivity and lowered the price of cloth. As the demand for cloth was relatively price elastic, the overall demand for cloth products increased, which led to a net gain in employment.

Referring to the observation made by Gordon Moore, co-founder of Intel, that the processing power of computers increases exponentially while their relative cost decreases at a similar rate.

The Future of technology and work

In recent years, a number of studies have aimed to assess the implications of automation for the labour market. Studying the United States' labour market, Frey and Osborne (2013) estimate that 47% of all occupations are at risk of automation. Using skills information from the Occupational Information Network (O*NET) database, they apply a machine-learning algorithm to determine the likelihood of specific skills becoming automated. Occupations with a relatively high share in automatable skills end up having a higher likelihood of being negatively affected by automation.

In their original study, Frey and Osborne focus on a small subset of skills that they deem to be barriers to automation. However, their work sparked a host of follow-up research aimed at refining the approach. For example, Arntz et al. (2016) find that, within a given occupation, employees often specialize in tasks that are more difficult to automate. Their results suggest that task variation significantly lowers the likelihood of being negatively impacted by automation and, that across Organisation for Economic Co-operation and Development (OECD) countries, only around 9% of occupations are at risk from technological change.

When considering the potential impact of automation on the labour market, then, it is important to keep in mind that automation disrupts occupations by replacing the tasks they are composed of (see Figure 3 for definitions).

An ability, whether learned or inherent, that facilitates the learning, acquisition and application of knowledge. Certain skills require learned procedures; others are abstract. Skills that can be acquired through learned procedures are easier to automate, as human procedures can be translated into computational ones.



The application of skill and knowledge to complete a goal. If a task requires only skills that are procedural, the task is routine. If a task requires skills that are abstract, the task is non-routine, as the procedure varies in some abstract way to complete the goal.

For this discussion, we classify occupations consistent with the Standard Occupational Classification system for labour market information. An occupation can be automated only if substantively all of the tasks required to perform it can be completed without a human. Autor et al. (2003) provide a helpful framework for distinguishing tasks that are relatively easy to automate compared to tasks that are more resilient to automation (see Figure 4).

FIGURE 4: Employment Classification Grid. Source: Autor et al. (2003).

	Routine	Non-Routine
Manual (blue-collar)	Production Crafts Operative Repair	Food Service Personal Care Protective Services
Cognitive (white-collar)	Clerical Administrative Sales	Professional Technical Managerial
Low Skill	Middle Skil	I High Skill

Following the employment classification grid displayed in Figure 4, routine tasks are most susceptible to automation as machines or smart software can readily replicate them. Non-routine tasks, on the other hand, are less easy to automate. Autor et al. (2003) and Cheremukhin (2014) distinguish between non-routine manual and non-routine cognitive tasks. Non-routine manual tasks are commonly characterized by a high degree of social interaction and relatively low skill demand, and are required for jobs in personal care, food services and protective services for example. Non-routine cognitive tasks are commonly characterized by higher order thinking, such as critical thinking, creativity and innovative thinking.

When assessing the potential impact of automation on the labour market, it is essential to break down occupations by their respective task contents. Occupations with a relatively high share of routine tasks are more likely to be negatively impacted by automation than occupations with a relatively high share of non-routine cognitive and non-routine manual tasks. This helps to inform which skills will be more relevant for the future of work and which skills will likely become obsolete. In other words, automation affects the nature of work itself, rather than replacing entire occupations at a large scale.



Related Studies

Researchers have recently begun using the skills and task-based approach to predict what industries and occupations will be most affected by automation over the coming decades. Manyika et al. (2017) analyze the potential impact of automation on the US job market and find that the automation risk of predictable physical activities threatens to disrupt manufacturing and retail trades in particular. They also find that data collection and processing activities are at risk of automation, which has implications across all sectors.

In a related study covering labour markets in the United States and the United Kingdom, Bakhshi et al. (2017) use an expert panel to train a machine-learning algorithm that predicts whether any given occupation will experience increasing, decreasing or unchanged demand for labour through 2030. In the US, they predict an increase in demand among occupations in education, personal care, construction trades and business operations, and a decrease in demand for financial specialists, retail sales workers, entertainment attendants, and transportation workers. In the UK, they expect to see growth in health and education occupations, as well as in food preparation, elementary services, hospitality and leisure services, sports and fitness, electrical and electronic trades, and creative, digital design, and engineering occupations. Meanwhile, they project decreasing demand for occupations in manufacturing production, administrative services, secretarial and sales services, customer services, and construction and building trades. The research conducted by Bakhshi et al. (2017) reveals that, while there are certain commonalities across countries, specific national contexts may lead to differing predictions about the demand for future labour.

Stackhouse et al. (2018) have conducted some research in the Canadian context. They predict that foundational skills will be the most in demand through 2021. These skills include active listening, speaking, critical thinking, and reading comprehension. Next come social skills (coordination and social perceptiveness), followed by analytical skills (judgment and decision-making). Stackhouse et al. project a surplus of labour in occupations that involve serving and supporting people's wants and needs. These occupations include opticians, payroll clerks, customer service representatives, administrative assistants, ride-sharing service drivers, drone operators, and mail workers. Meanwhile, they predict labour shortages in occupations that provide specialized services, as well as in occupations that involve innovation and finding solutions to intractable problems. The former group includes pharmacists, nurses, social media managers, bloggers, real estate agents, chefs and police officers, while the latter includes legislators, architects, doctors, judges, driverless car engineers, mechanics, data scientists, and cloud computing specialists.

Using standard occupation and industry taxonomy, Oschinski and Wyonch (2017) assess the impact of automation on Canadian industries. Their findings suggest that industries with relatively higher shares of routine occupations—such as accommodation and food services—are likely to be more negatively affected than industries with relatively low shares

Employment ('000) Percent 2500 100 90 80 2000 70 1500 60 -50 40 1000 30 500 -20 10 0 0 Construction Computer System Design Services Management, Scientific and Technical Services **Educational Services** Wholesale Trade **Oil and Gas Extraction** Finance, Insurance, Real Estate and Learning Utilities Other Services Support Activities for Mining and Oil and Gas Extraction Other Transportation Equipment Manufacturing **Retail Trade** Fishing, Hunting and Trapping Other Professional Services Health Care and Social Assistance **Professional Business Services** Public Administration Information, Culture and Recreation Computer, Electronic and Electrical Products Management, Transportation and Warehousing Forestry and Logging with Support Activities **Rubber, Plastics and Chemicals** Other Manufacturing Metal Fabrication and Machinery (excluding electrical) Printing and Related Support Activities Wood Product Manufacturing Mining and Quarrying (except oil and gas) Manufactured Mineral Products Food and Beverage Products Paper Manufacturing Motor Vehicle, Body, Trailer and Parts Manufacturing Agriculture Accommodation and Food Services Administrative and Other Support Unknown (suppressed in data) Employment at high risk Percent of employment at high risk Employment at low or medium risk

FIGURE 5:

Vulnerable Employment by Industry in Canada. Source: Oschinski and Wyonch (2017)

of routine occupations, like educational services. As Figure 5 shows, retail trade, the second largest industry in Canada based on the total number of employees, has a share of vulnerable employment of around 50%. Accommodation and food services, a sector employing around 1.2 million people, has a share of vulnerable employment of around 70%.

It is important to note that this does not mean that these vulnerable occupations will all be fully automated. In this context, "vulnerable" means that these occupations have a higher likelihood of being negatively impacted by automation because they include tasks that are at risk of being automated. The current consensus on the impact of automation on the labour market suggests that retraining, upskilling and lifelong learning will become key to keeping the labour force resilient to continuous technological change. A recent OECD report indicates that roughly one in four adults exhibits a mismatch between their existing skill sets and their actual job requirements (McGowan and Andrews 2015). Yet, what is largely lacking in current research is an approach to identifying viable pathways to inform job seekers, policy-makers, employment agencies, and employers about opportunities to transition out of occupations that are at risk of automation and into those that are more resilient (World Economic Forum 2018). The World Economic Forum (WEF) paper "Towards a Reskilling Revolution" (2018) is most closely related to our research. The paper defines job transition pathways for select occupations in the United States, using labour market data from the US Bureau of Labor Statistics (BLS) alongside job characteristic information from O*NET and Burning Glass Technologies. Using BLS employment projections through 2026, the WEF identifies examples of starting jobs in the job families that are expected to experience significant disruption (like office and administrative roles). They then determine target jobs based on occupational similarity scores calculated by taking into account factors such as the skills, experience and education required for specific occupations. Applying the pathways approach to the Canadian context, we present an illustrative model that would eventually allow people to explore their career transition options. This report is the first in a series of in-depth research papers outlining potential employment pathways for various occupations, enabling all Canadians to benefit from the digital revolution.







Industries and occupations are dynamic and, as a consequence, the nature of work is ever changing. Governments must be proactive about shifts in the labour market in order to preempt the frictions that threaten to displace workers from their jobs. However, governments should not be solely responsible. Individuals and employers should be aware of how labour market disruptions might impact them and should be prepared for the future of work.

Navigating these changes successfully will require employment agencies, educational institutions and policy-makers to work with employers and workers to ensure that all individuals have access to the information and support needed to build viable lifelong careers. These groups have always played a role in connecting people with jobs, but have often neglected to consider whether jobs are sustainable in the long run. As such, there is a need for a coordinated effort to build a workforce that is resilient to disruption, which today is being driven in large part by automation.

Part of the solution involves helping workers to develop skills that are difficult to automate and to transition into jobs that are intensive in such skills. Our employment pathways aim to define these transitions.





Employment pathways defined

An employment pathway is the mapping of a job transition that begins at a starting job and flows to various target job options, noting the upskilling and retraining required in order to move from one job to the next. By detailing skills gaps, sharing training program information, and profiling each occupation, employment pathways provide workers with career options to choose from, along with the guidance they need to reach their targets.

To ensure that the proposed transitions are feasible, starting jobs lead to target jobs with which they share a reasonable number of attributes and which have both a substantial demand for labour and a comparable or higher median salary. Each target job may in turn flow to further target jobs in order to provide an expanded set of alternatives. As our employment pathways are designed to address automation in the labour market, we also require automation risk to decrease when moving from starting to target jobs.

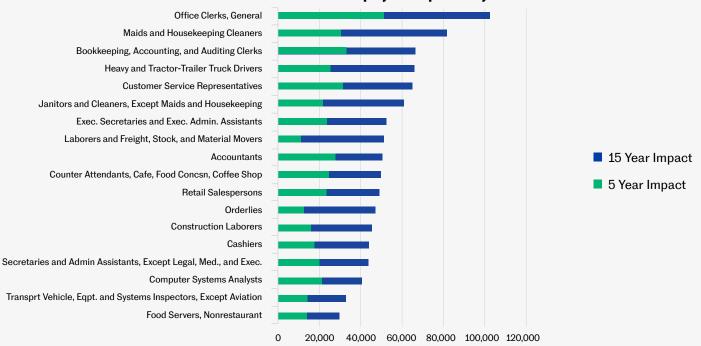
Our application of the pathways approach centres on the idea of automation; however, employment pathways can also be used as a general purpose tool to help workers navigate career transitions for any number of reasons. Further, educational institutions, employment agencies, employers, and governments can use the mappings to inform the creation of policy and programs that are designed to train, advise, and support workers. Finally, the pathways approach can be applied to diverse geographic regions and demographics. As we expand the Employment Pathway Program for Canada and move through various iterations, we will continue to explore the variety of applications of the pathways approach.

Methodology

We illustrate our employment pathways as interactive visualizations with the aim of presenting the information in an intuitive, user-friendly format. To determine our starting and target jobs, we partnered with Faethm.ai, whose two-part model uses expert insights and support vector clustering (SVC) to predict the automation risk of occupations and group jobs that are closely related based on their attributes (skills, knowledge, abilities, activities, and context).

How do we choose the starting jobs?

We prioritize three occupations to serve as starting jobs for our example pathways, based on employment statistics and automation risk. To ensure our examples are relevant, we choose three of the highest employing occupations in Ontario, all of which are at a high to medium risk of automation. Automation risk is determined by the model, which assigns a risk rating to every occupation in the province. Occupations are matched to their attributes and the risk rating is calculated based on how susceptible each attribute is to automation. The rating is on a zero-to-one scale, representing the proportion of job attributes that are predicted to become automated over the next 15 years. The SVC algorithm is trained based on labour demand predictions made by a community of experts, and the predictions are weighted according to the accuracy of each expert's past predictions. Five- and fifteen-year impact of automation expressed in number of employees. Ontario workers aged 25-64.



Number of Employees Impacted by Automation

How do we identify our target jobs?

To ensure our pathways represent feasible transitions, we use the model to match starting jobs to target jobs. Jobs are matched based on the attributes they have in common. This information is used to identify the most feasible target jobs according to ease of reskilling. We also consider median salary, labour demand, and the automation risk of the target jobs, to ensure our pathways include viable career transition options.

Our methodology relies on a few key assumptions. At this point, the platform is not customizable to specific workers' skill sets, so we must assume that the people working in the starting jobs have the skills and knowledge required for those jobs. Similarly, we assume that they lack the skills required for the target jobs. Further, due to the scope of this report, we assume that people can transition between industries as long as they are moving to a target occupation that closely matches their starting job. We plan to look more closely at specific industries in further research. Finally, we base our analysis on jobs that currently exist, rather than attempting to predict the creation of new jobs. While we recognize that occupations change over time and that net new occupations and tasks will be borne out of technological change, making these predictions involves a high degree of uncertainty and is therefore out of scope for this report.

Data

We use the O*NET database of occupation-specific descriptors to match each occupation to its associated skills, abilities, knowledge, work activities, and work context. O*NET contains descriptions of nearly one thousand occupations. It is the most widely used source of information on occupational characteristics in the United States and is recognized worldwide.

Our employment data comes from the 2016 Canadian Census, administered by Statistics Canada. It includes employment and median income by the four-digit National Occupational Classification (NOC) and the four-digit North American Industry Classification System (NAICS). The data is aggregated to the Census Metropolitan Area level and grouped by age range and sex. To interpret the Canadian data in terms of the Standard Occupation Classification (SOC) system, we rely on a mapping of NOCs to SOCs provided by Faethm.ai.

Finally, our labour demand data comes from Burning Glass Technologies² and CEB TalentNeuron, two web analytics platforms that aggregate data from job boards and company career sites. They map jobs to NOCs based on the information included in job postings. This data gives us an idea of the demand for labour in each of our pathway jobs.

^{2.} Accessed through the job insights tool on the Ontario Ministry of Training, Colleges and Universities website.

FIGURE 7:

Employment by Occupation and Sex. Ontarians aged 25-64. Data from 2016 Census of Canada.

Employment by Occupation & Sex

Industry	<u>}</u> Male	R Female	Total
Heavy and Tractor-Trailor Truck Drivers	73,695 (97%)	2,225 (3%)	75,920
Executive Secretaries and Executive Administrative Assistants	13,615 (14%)	80,800 (86%)	94,415
Retail Salespersons	57,910 (43%)	75,880 (57%)	133,790

Examples

Our three example pathways present career transition options for the working age population (aged 25 to 64) in Ontario. Each example pathway flows from a starting job to three alternative target jobs. One target job in each pathway then flows to three further target jobs. The starting jobs are at high and medium risk of being disrupted by automation over the coming 15 years, while the target jobs are at lower risk.

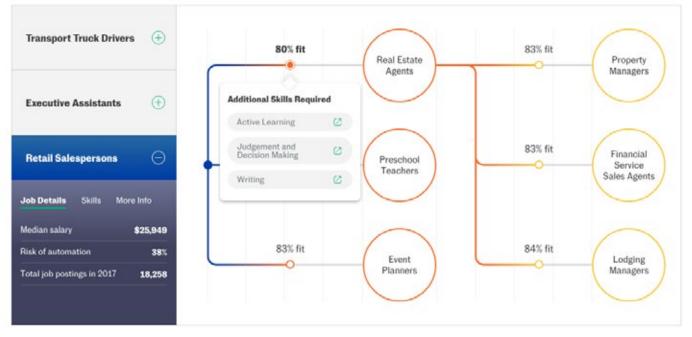
As our three example starting jobs, we have selected: 1) heavy and tractor-trailer truck drivers; 2) executive secretaries and executive administrative assistants; and 3) retail salespersons. Based on data from the 2016 Canadian Census, these occupations combined employ a total of 304,125 working age Ontarians and, as is consistent with the literature, are expected to be among the occupations most impacted by automation over the coming 15 years (see Figure 6). The jobs represent a diversity of industries, with heavy and tractortrailer truck drivers working primarily in transportation and warehousing, executive secretaries and executive administrative assistants working in public administration, as well as in finance and insurance, and retail salespersons working primarily in retail trade. Our starting jobs have high to medium automation risk ratings and varying proportions of male and female employees, which implies that automation will impact men and women disproportionately in some cases (see Figure 7).

Heavy and tractor-trailer truck drivers are assigned a 90% risk rating, with a predicted automation impact on 25,113 working age employees over the next five years and 68,272 over 15 years. This is consistent with the expectation that self-driving vehicles will affect the transportation industry, as suggested by Stackhouse et al. (2018), who foresee an increase in demand for driverless car engineers in Canada, as well as Bakhshi et al. (2017), who predict a decreasing demand for transportation workers in the United States.

Executive secretaries and executive administrative assistants are at a 60% risk of automation, with a predicted five-year impact on 26,944 workers and a 15-year impact on 56,483 workers. The WEF (2018) chooses a similar starting occupation, secretaries and administrative assistants, for one of its pathways, noting that employment in office and administrative roles in the US is expected to decline significantly through 2026. Our final example starting job, retail salespersons, has an automation risk of 38%. This occupation has the highest level of employment among working age Ontarians, with 133,790 workers, according to the 2016 Census. The model predicts 23,445 retail salespersons will be impacted by automation over the next five years and that this number will climb to 51,401 after 15 years. These findings are consistent with those of Oschinski and Wyonch (2017), who find that roughly 50% of Canada's retail trade industry is vulnerable to automation, and of Bakhshi et al. (2017), who predict a decline in demand for retail salespeople in the United States.

FIGURE 8: Example pathway for retail salespersons

The Employment Pathway Platform helps individuals navigate the future of work by providing access to the information and support they need to build viable, lifelong careers. This demo displays what 3 possible career pathways towards roles at a lower risk of automation could look like.



Fit percentage is a weighted average based on transferability and difference in the level of skills, abilities, knowledge, and work context from one role to another.

As retail salespersons sales is the highest employing occupation among working age Ontarians, we will use this particular example to further discuss employment pathways in practice (see Figure 8). Our three target jobs for retail salespersons are: 1) preschool teachers; 2) meeting, convention and event planners; and 3) real estate sales agents. The O*NET profiles for these occupations provide evidence of their commonalities with retail sales jobs. In particular, each of the target occupations relies heavily on social interaction, as do retail sales roles. Speaking, active listening and coordination are considered highly important skills for all four of these jobs, while customer and personal service is the most important area of knowledge for three out of four of the jobs (it is the second-most important area of knowledge for real estate sales agents). Similarly, oral comprehension and oral expression are the top two required abilities across these jobs. Communicating with people outside of the organization is a main work activity for each of the jobs, and having contact with others (specifically face-to-face discussions) is a key element of their work contexts.

The common interpersonal element between retail salespersons and the three target jobs makes the transition between these roles feasible. But are these transitions viable? Preschool teachers, meeting, convention and event planners, and real estate sales agents have automation risk ratings of 9%, 6%, and 23%, respectively. These risks are substantially lower than the 38% assigned to retail salespersons. Further, according to the 2016 Census, each of the three target jobs boasts a higher median annual salary than the starting job.

To ensure our pathways present viable options, we must also consider how the demand for workers across the target jobs compares to the number of workers employed in the starting job. According to data aggregated from job boards in 2017 by Burning Glass Technologies, there were 4,338 job openings last year in Ontario across the three aforementioned target jobs. It is worth noting that we only represent a subset of viable target jobs in our pathways, so this figure is a lower bound. However, in order to provide additional options, we match real estate sales agents, the highest risk target job, to three further target jobs: 1) property, real estate and community association managers; 2) financial services sales agents; and 3) lodging managers. As in the first level of the example pathway for retail salespersons, this second level matches real estate sales agents to jobs that can be feasibly attained. In 2017, there were 4,042 job postings for these three additional jobs. This brings the total postings for example target jobs to 8,380.

A full employment pathway would have further target jobs branching out from each original target job, resulting in a map that presents more options for workers to choose from. While our example pathways illustrate select career transitions, we can use the pathways approach to build out more robust networks as we expand the Employment Pathway Platform for Canada.

Conclusions and Next Steps

The technological advancements of the Fourth Industrial Revolution have significantly changed the way we work and will continue to do so in an accelerated manner. While some jobs are at risk of being completely automated, there are many jobs where the evolution of technology will lead to the augmentation of existing jobs and even the creation of new jobs.

In any of these cases, we should be prepared for the changing nature of work. The World Economic Forum has identified the need for a pathways model to provide job seekers with access to accurate information about the implications of automation, along with actionable insights and long-term solutions. By building on the methods outlined in this report, we at MaRS aim to address this need by determining the effects of technological change on the labour force and presenting a scalable model that can be used to outline employment pathways in the Canadian economy. This analysis will be the core of the Employment Pathway Platform, a tool that provides users with viable career transition options and detailed information on how to navigate these transitions.

While a fundamental goal of our tool is to support individual job seekers and employers, we believe that the tool will also be valuable to other user groups. Educational institutions, governments and employment agencies will all have a role to play in mitigating the risks and effects of automation on the Canadian workforce. These groups may use the platform to better understand the contributing factors that put current occupations at risk of automation, increase awareness with regard to emerging occupations that leverage automation, and identify existing skill gaps in the labour force. For intermediaries such as educational institutions and employment agencies, the tool could help guide the development of training programs and the career advice they provide. For policy-makers, understanding future trends and labour market trajectories as well as the underlying skills gaps—can help them to efficiently allocate resources to support individuals and organizations actively trying to overcome these gaps.

Over the next few months we will be further developing and testing our research methodology to integrate additional data and improve our employment pathways model. Meanwhile, we will continue to build partnerships with key stakeholders in this space. With the Employment Pathway Platform, our aim is to provide a versatile tool backed by robust evidence and cutting-edge research to help individuals and organizations make informed decisions in the context of ongoing technological change.

References

Arntz, M., Gregory, T. and Zierahn, U. (2016).

The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. OECD Social, Employment and Migration Working Paper No. 189. Paris: OECD. http://dx.doi.org/10.1787/5jlz9h56dvq7-en.

Arthur, W. B. (2011). The nature of technology: What it is and how it evolves. New York, NY: Penguin.

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical investigation. Quarterly Journal of Economics, 118, 1279-1333.

Bakhshi, H., Downing, J. M., Osborne, M., & Schneider, P. (2017). The future of skills: Employment in 2030. London: Pearson and Nesta. <u>https://www.nesta.org.uk/report/the-future-of-skills-employment-in-2030/</u>.

Bessen, J. (2016). How computer automation affects occupations: Technology, jobs, and skills. Boston University School of Law, Law and Economics Research Paper, 15-49.

Bessen, J. (2015). Learning by doing: The real connection between innovation, wages, and wealth. New Haven, CT: Yale University Press.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. New York, NY: WW Norton.

Cheremukhin, A. (2014). Middle-skill jobs lost in U.S. labor market polarization. Economic Letter, 9(5), 1-4.

Cowen, T. (2013, August 13). Who will prosper in the new world. New York Times. Retrieved from <u>https://opinionator.blogs.</u> <u>nytimes.com/2013/08/31/who-will-prosper-in-the-new-world/</u>

Faethm. (2018). Tandem.ai analytics engine [Software]. Available from <u>https://faethm.ai/</u>

Frey, C. B., & Osborne, M. A. (2013). The future of employment: How susceptible are jobs to computerisation? Oxford Martin School, Programme on the Impacts of Future Technology, University of Oxford. Retrieved from <u>http://www.oxfordmartin.</u> <u>ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf</u>

Krugman, P. (2013, June 14). Sympathy for the Luddites. New York Times. Retrieved from <u>https://www.nytimes.</u> com/2013/06/14/opinion/krugman-sympathy-for-theluddites.html

Levy, F., & Murnane, R. J. (2004). The new division of labor: How computers are creating the next job market. Princeton, NJ: Princeton University Press.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). A future that works: Automation, employment, and productivity. McKinsey Global Institute Executive Summary. Retrieved from <u>https://www.</u> <u>mckinsey.com/featured-insights/digital-disruption/harnessing-</u> <u>automation-for-a-future-that-works</u>.

References Continued

McGowan, M. A., & Andrews, D. (2015). Skill mismatch and public policy in OECD countries. OECD Economics Department Working Paper No. 1210. Paris: OECD.

Miller, B., & Atkinson, R. D. (2013). Are robots taking our jobs, or making them? ITIF Publication. Retrieved from http://www2.itif.org/2013-are-robots-taking-jobs.pdf

Ministry of Advanced Education and Skills Development. (2017). Search job profiles, Ontario's labour market. Accessed July 2018. Retrieved from <u>https://www.iaccess.gov.on.ca/labourmarket/search.xhtm</u>

Occupational Information Network. (2018). O*NET database version 22.3. Retrieved from <u>https://www.onetonline.org/</u>

Oschinski, M., & Wyonch, R. (2017). Future shock? The impact of automation on Canada's labour market. C. D. Howe Commentary No. 472. Retrieved from <u>https://www.cdhowe.org/sites/default/files/attachments/research_papers/mixed/Update_Commentary%20472%20web.pdf</u>

Schwab, K. (2016). The fourth industrial revolution. World Economic Forum.

Sirkin, H.L., Zinser, M., & Hohner, D. (2011). Made in America, again: Why manufacturing will return to the U.S. Boston Consulting Group. Retrieved from <u>http://www.bcg.com/</u> <u>documents/file84471.pdf</u> Stackhouse, J., Borra, J., Klimbovskaia, A., & Aulthouse, A. (2018). Humans wanted: How Canadian youth can thrive in the age of disruption. Royal Bank of Canada. Retrieved from <u>https://www.rbc.com/dms/enterprise/futurelaunch/humans-</u> <u>wanted-how-canadian-youth-can-thrive-in-the-age-</u> <u>of-disruption.html</u>

Statistics Canada. (2016). 2016 census of Canada employment and median income by occupation, industry, age, sex, and census metropolitan area [Data file]. Ottawa.

World Economic Forum. (2018). Towards a reskilling revolution: A future of jobs for all. World Economic Forum Insight Report in collaboration with Boston Consulting Group. Retrieved from <u>http://www3.weforum.org/docs/WEF_FOW_</u> <u>Reskilling_Revolution.pdf</u>