

Field of Study and Occupational Mismatch: How has Employment Been Affected by  
Computerization in Canada?

By  
Jiale Li

A Thesis Submitted to  
Saint Mary's University, Halifax, Nova Scotia  
in Partial Fulfillment of the Requirement for  
the Degree of Bachelor of Commerce

December 2017  
Halifax, Nova Scotia

© Jiale Li, 2017

Approved: \_\_\_\_\_  
Dr. Yigit Aydede  
Associate Professor

Approved: \_\_\_\_\_  
Dr. Mark Raymond  
Department Chair

Date: \_\_\_\_\_

Field of Study and Occupational Mismatch: How has Employment Been Affected by  
Computerization in Canada?

By  
Jiale Li

A Thesis Submitted to  
Saint Mary's University, Halifax, Nova Scotia  
in Partial Fulfillment of the Requirement for  
the Degree of Bachelor of Commerce

December 2017  
Halifax, Nova Scotia

© Jiale Li, 2017

Approved: Dr. Yigit Aydede  
Associate Professor

Approved: Dr. Mark Raymond  
Department Chair

Date: \_\_\_\_\_

Field of Study and Occupational Mismatch: How has Employment Been Affected by  
Computerization in Canada?

by Jiale Li

**Abstract**

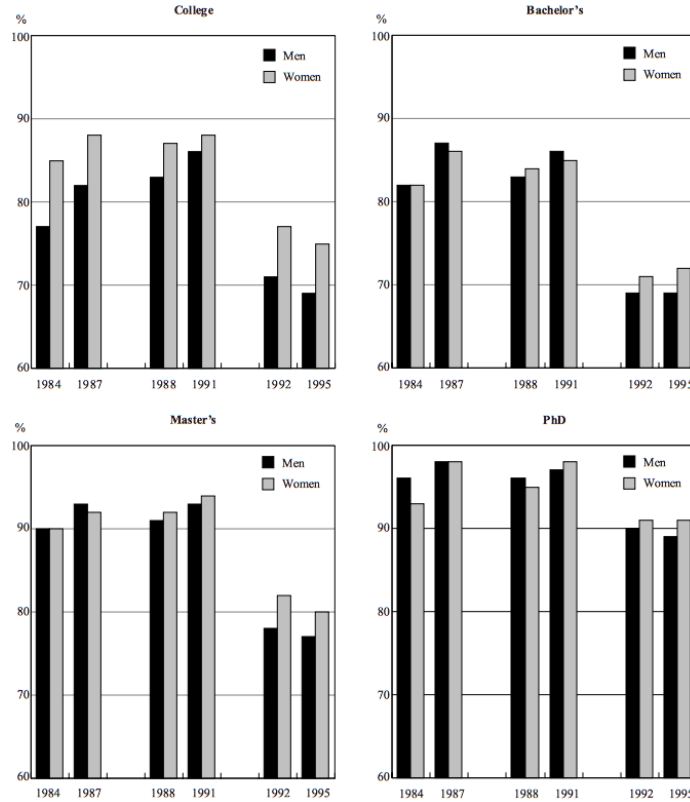
Nowadays, technology is a necessity for people because it serves a variety of functions in the modern society and has improved significantly the living standards compared to what they were 100 years ago. Although a lot of people obsess about how these amazing advanced technologies can easily handle logistic tasks and make their life easier and better, there are still a lot of researchers and experts who have critiqued the existence of emerging technology. They insist that machine learning technology is not as good as it appears because computerization and digitalization stand a good chance of replacing the human capital and thus a great amount of occupations will face different degrees of computerization risk. In this paper, data sources from Statistic Canada Public Use Microdata File were gathered and the dataset used for analysis is the 2011 National Household Survey. In addition, the author reviewed a large number of articles that mentioned the impact of computerization and how machine learning would displace occupations and further accelerate the mismatch between field of study and occupations. This study examined Frey and Osborne's (2013) study and categorize occupations into three degrees of computerization risk, which are low, medium and high and it also uncovers how machine learning assuredly increase the mismatch rate for the field of study in relation to the medium risk occupations. The purpose of this paper is to estimate how automation and computerization can destroy a large number of occupations and force the workers into irrelevant areas.

Date: \_\_\_\_\_

## **Introduction**

The first fiction movie to focus on artificial intelligence was introduced in 1927. The high technology and advanced artificial intelligence shown in the movies inspired humans to imagine what our future world could be like. Recently, many scientific institutions and technical corporations such as IBM and Google mainly focused on developing emerging technologies by improving artificial intelligence and machine learning. Their targets are to create an ever more practical world for the future and our imaginations about future advanced technology and innovations are becoming ever more realizable in the near future. The significant growth of technology over the past few decades have influenced the younger generations' decision to pursue a post-secondary education. Governments, especially those in developed countries, have encouraged the pursuit of higher education to stimulate economic growth and further spur the general wellbeing of society, as increases in higher education levels can spread new educational concepts and create innovation in this new era of science and technology (Te Riele & Crump, 2003). This growth in technology has led to the assumption of high demand for high degree holders, encouraging more people to pursue university degrees. Therefore, the growth in bachelor's degree holders has been increasing much faster than the number of jobs requiring bachelor's degrees, so the ineffective labor market and educational system are unable to assist every higher education graduate with finding a match occupation, causing two necessary mismatches, which are field of study-occupational mismatch and education-occupation mismatch.

**Figure 1. Index of Job Requirements: Educational Match**



Source: National Graduates Surveys

Figure 1 indicates the four education levels in the educational-occupational skills match, mainly focusing on the skilled prerequisites for a specific occupation and comparisons between the graduate's educational backgrounds and the education level required by the job. The educational and occupational match has been continuously declining in terms matching level between 1984 to 1995. The figure illustrates an increasing gap in education-skill mismatch for bachelor and master degree holders between 1984 to 1995. The figure below shows 80% of male master degree holders can find a matching job after graduation, with around 30% of bachelor degree holders trying

to find jobs that can match their skills. This demonstrates that bachelor and master degree holders are losing their capacity to find an occupation that can match their education levels, which forces them to apply for irrelevant occupations.

The mismatch between field of study and occupation has also been dramatically increasing over the past decade. According to Ghaffarzadegan, Xue, and Larson (2014), the primary victims of this mismatch are the STEM workforce. STEM is defined in Statistic Canada as a group of university graduates who majored in the “science, technology, engineering, mathematics, and computer science programs” (Ghaffarzadegan, Xue, and Larson (2014) for their postsecondary education. The rapid growth in the higher education labor market and acceleration of changes in the information technology era has driven more demand for STEM degree holders, which should lead to a better match with the STEM field of study compared with other non-STEM programs. However, the existing mismatches in the job market has exhibited a reverse result, which indicates the inefficiency of postsecondary study as it has become worthless and incapable of matching jobs with university graduates.

**Table 1. Labor Market Outcomes for STEM Graduates**

Labor market outcomes of university graduates aged 25 to 34, by sex and major field of study, 2011			
	Total	Women	Men
	percentage		
<b>Unemployment</b>			
Total STEM	5.5	7	4.7
Science	6.2	6.6	5.8
Technology (excludes engineering technology)	5.1	3.4	6.7
Engineering	4.9	7.1	4.3
Mathematics and computer science	5.4	8.5	4.2
Non-STEM	5.6	5.7	5.5
<b>Skill mismatch<sup>1</sup></b>			
Total STEM	14.3	18.3	11.8
Science	18	18.9	16.8
Technology (excludes engineering technology)	22.2	20.5	23.5
Engineering	10.6	13.5	9.8
Mathematics and computer science	13.6	22.4	10.1
Non-STEM	19.7	18.5	22.2

Source: Statistics Canada, National Household Survey, 2011.

Table 1 illustrates the labor market outcome for STEM graduates aged 25 to 34 who are hired for an occupation that does not require their current educational certificate. Table 1 shows the total technology and science graduates respectively have 22.2% and 18% who are mismatched, which is above the total STEM mismatch rate. This indicates the technology and science graduates face great difficulties in finding occupations that require their university educations and were employed in jobs requiring high school educations or less (Statistic Canada). This result verifies an outcome that is the complete opposite of the Canadian government's expectations as Canada's national innovation

---

<sup>1</sup> The percentage of occupations require obtaining a high school diploma or less. This includes people who were employed during the NHS reference week, or were unemployed but did work in 2010 – 2011.

strategies encourage university students to choose STEM programs because technological advancement will demand a larger STEM workforce. Moore's law states computing power will double every two years starting from 1958. Moore insisted the fast growth of technology requires a workforce of highly educated individuals. However, the existing skill mismatch in the STEM workforce does not strongly support Moore's opinion.

To understand the field of study and occupational mismatch requires an analysis of the origins of the consequences. In this paper, I will focus on how jobs susceptible to computerization will affect the field of study and job match rate, and also widely discuss the other potential factors that could negatively affect the match rate.

### **Literature Review of the Relationship Between Employment and Computerization**

Society as a whole is creating an atmosphere in which the existence of machines is negatively affecting the human labor market at this moment. Armtz, M. T. Gregory, and U. Zierahn (2016) studied the total share of employees at high risk after 70% of automation is applied in the world. They indicated German and Austrian workers have the highest risk (12%). Whereas, Korea workers had the lowest risk (6%). US workers have 9% of occupations at high risk of being affected by automation and this number is as same as all countries on average. The share of workers at high risk of unemployment due to automation does not illustrate the details such as the occupational categories, fields of industries, or number of workers at high risk affected. A deep exploration of which field has the largest share of employees at high risk requires all fields of work that contain some share of computerization be listed.

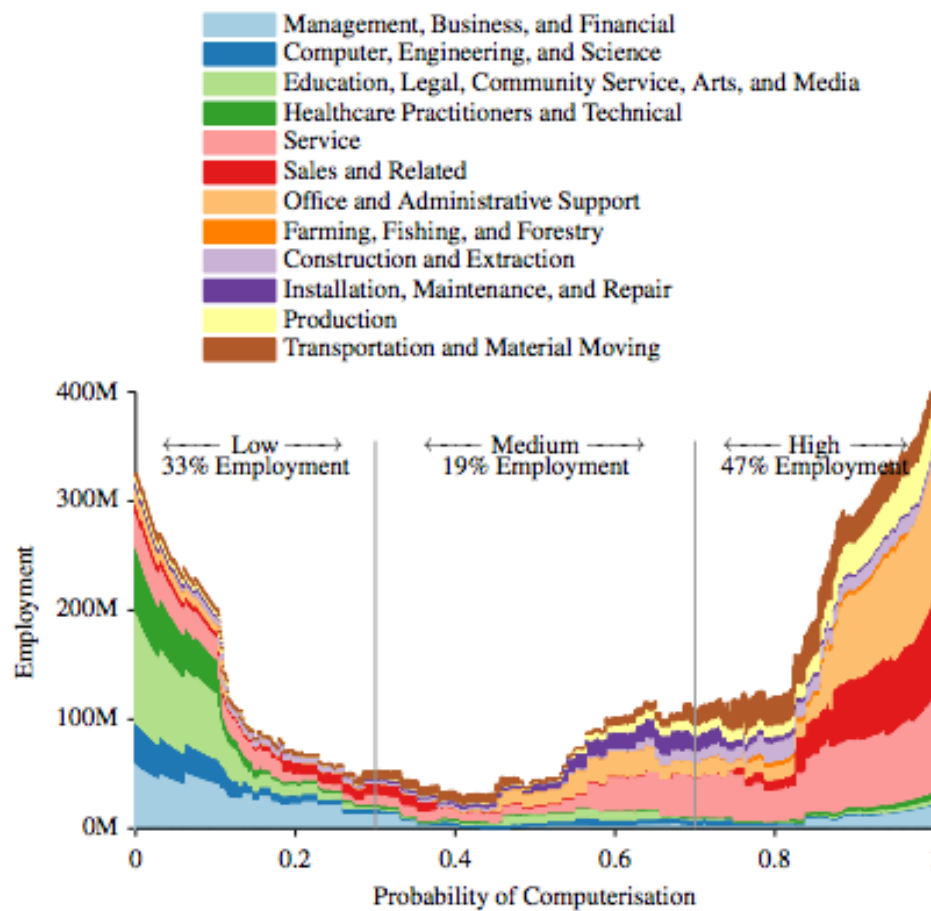


Frey and Osborne (2013) published an article on how occupations will possibly be computerized, providing an estimated 702 detailed jobs in the United States. Many scholars use evidence to indicate how computer-controlled equipment will be a reasonable explanation for jobless growth in the future and the impact of computerization on the labor market is well explained in these scholars' studies, documenting how routine intensive occupations is declining and being replaced by machines. The ongoing decline in manufacturing occupations and the disappearance of some routine with low communication jobs are influencing the employment rate of the whole labor force. Considering that advanced technology is related to falling prices with problem-solving skills and productivity that are more competitive compared with humans, thus, analyzing the future of current occupations with a degree of computerization can lead to a better understanding of the probability of employment growth that is highly sustainable or replacement by certain machines.

Frey and Osborne (2013) separated the occupational computerization on three levels. The jobs lacking in social intelligence and creativity had the occupations with the highest degree of computerization. Lacking social intelligence means the individuals do not require any talent or education before taking the job, such as cashiers, and counters. The computerization of occupations in the medium category showed the slowdown of the labor market is because these jobs are somehow influenced by machines. In the medium computerization category, the risk mainly depends upon higher "manual dexterity," higher "finger dexterity," and "limited work space" with no need for communication. Nevertheless, the tasks require high degree of communication, professional knowledge,

management skills and innovation have lowest susceptibility that cannot be substituted by machine learning.

**Figure 1. Employment Affected by Computerization in the United States**



Source: Frey and Osborne (2013), The Future of Employment: How Susceptible Are Jobs to Computerization? University of Oxford.

Frey and Osborne (2013) focused on figuring out the potentially risky occupations in the USA that are threatened by computerization and automation and analyzed how jobs are susceptible to computerization in the twenty-first century. Figure 2 presents the characteristics of occupations and finds a substitute relationship between 632 jobs in the US and computerization. Figure 1 has three sections, which are: low risk (less than 30%), medium risk (30%-70%), and high risk (greater than 70%). Frey and Osborne (2013) claimed 47% of jobs in the United States face a potentially high risk of easy replacement by automation within the next decade or two. This figure indicates occupations such as transportation, logistics, and labor in production departments will most likely be substituted by computerization. Surprisingly, occupations like service, sales, and office support jobs fall under the high-risk category. Frey and Osborne (2013) believe the risk of automation is higher for routine, unskilled, and low wage jobs because industrial robots and automation are becoming more advanced and efficient, albeit at a slow pace. Frey and Osborne (2013) and Armtz, M. T. Gregory, and U. Zierahn (2016) both mentioned the potential high risk of employment for Americans, but the percentage of high risk is quite different as it is between 9% and 47%. In Frey and Osborne's discussion, their only concern was for occupations rather than for industries that still have many tasks that can be done by machine or not, which means Frey and Osborne (2013) might have overestimated the capabilities of computerization. People might place too much trust in machines and overstate the capability of robots, being misled by the common sense that robots are always effective and flawless.

## **Data and descriptive analysis**

In this paper, the dataset analyzed was collected from the Statistic Canada Public Use Microdata Files. This dataset, called the 2011 National Household Survey, includes information on the demographics as well as economic and social characteristics of people living in Canada. The dataset includes 887,012 observations, used cross-sectional design, and was tested during the 2011 Census. In order to obtain a more accurate result for the mismatches between the field of study and occupation as well as further contribute to exploring the mismatched occupations that are significantly related to computerization, I needed to limit the number of observations. I analyzed the dataset and excluded unwanted observations, such as aboriginal identity, members of age groups younger than 19 years old or older than 65 years old, the disposable annual income of less than \$2000, unpaid family workers, non-degree holders, and those not in the labor force. I controlled my observations to consist of those between 19-65 years of age in consideration of this age range being allowed to work by law. Only keeping the individuals who have more than \$2000 in disposable income means the exclusion of people who live under the minimum income level. Unpaid family workers should not be considered because they are free laborers and not economic resources. People without postsecondary certifications, degrees, or diploma holders represent individuals who did not have their specific field of study, which is irrelevant to my topic. The individuals not part of the labor force should be eliminated as they are not actively seeking employment in the labor market. The observations then dropped to 228,473 after I placed these restrictions.

The 2011 National Household Survey provides the detailed classification for each individual's study program such as the highest level of academic certification, diploma, or degree they obtained. Statistic Canada uses the Classification of Instructional Programs in 2011 (CIP2011) to classify the significant fields of study with 11 defined educational groups. The 2011 Census occupation data also uses the national occupation major classification 2011 (NOC11), which is composed of 30 different major occupational categories.

#### **Field of study and Occupational Mismatches Related to Computerization**

In this study, given the large amount of observations at my disposal, I applied frequency distributions similar to those used in the study by Aydede and Dar (2017) on the field of study to occupation relatedness, which allowed me to calculate the following clustering index:

$$RI = \frac{OF/F}{O/T}$$

Where O is the occupation, F is the field of study, and T represents the whole workforce. The relatedness index measures the workers who are employed in an occupation in their related primary area of study OF by calculating the percentage of workers in major F in the numerator. I calculated the number in the numerator and divided the number by the size of O in the whole workforce T. Then, using the frequency distributions of 11

different field of studies in which the individual obtained their highest certificate, diploma, or degree and their occupations among the occupational groups, including 30 primary sectors, in the occupational classification/ labor industry sector of North American industry.

The result of relatedness index (RI) reports how the degree of each worker's occupation matches with their post-secondary education. For better understanding, all the calculated relatedness index should be normalized between 0 and 1. For the observations' normalized RI are greater than 0.80 which means the worker's occupation is better matched with their field of study and vice versa. Tabulating NOC11 and CIP2011 by using these normalized RIs to indicate match ratio between 30 occupations and 11 fields of studies.

**Table 1 Distribution of field of study – occupation match ratio in Canada -2011**

Occupations	Education - Major Field of study										
	1	2	3	4	5	6	7	8	9	10	11
1	0.05	0.06	0.38	0.32	0.63	0.37	0.15	0.20	0.10	0.04	0.02
2	0.13	0.07	0.38	0.32	0.59	0.33	0.28	0.12	0.06	0.07	0.03
3	0.04	0.12	0.44	0.26	0.55	0.27	0.15	0.19	0.10	0.07	0.12
4	0.03	0.05	0.17	0.12	0.30	0.34	0.08	0.49	0.55	0.03	0.06
5	0.03	0.04	0.35	0.31	<b>1.00</b>	0.17	0.12	0.04	0.03	0.02	0.01
6	0.06	0.07	0.46	0.38	0.70	0.18	0.14	0.05	0.05	0.11	0.05
7	0.04	0.10	0.37	0.22	0.64	0.22	0.15	0.19	0.07	0.07	0.09
8	0.06	0.09	0.50	0.28	0.67	0.27	0.18	0.04	0.04	0.14	0.07
9	0.01	0.03	0.09	0.08	0.11	<b>1.00</b>	<b>1.00</b>	0.53	0.11	0.01	0.00
10	0.01	0.07	0.11	0.10	0.08	0.72	0.53	0.57	0.28	0.03	0.09
11	0.01	0.00	0.00	0.04	0.00	0.12	0.00	0.00	0.00	<b>1.00</b>	0.00
12	0.02	0.02	0.11	0.08	0.06	0.51	0.02	0.02	0.03	0.82	0.03
13	<b>1.00</b>	0.07	0.53	0.18	0.05	0.58	0.09	0.04	0.04	0.05	0.01
14	0.09	0.03	0.65	<b>1.00</b>	0.35	0.37	0.06	0.03	0.10	0.08	0.01
15	0.30	0.04	0.44	0.96	0.25	0.13	0.04	0.02	0.02	0.10	0.05
16	0.18	0.05	0.31	0.41	0.17	0.17	0.06	0.09	0.07	0.17	0.45
17	0.07	<b>1.00</b>	<b>1.00</b>	0.39	0.10	0.27	0.30	0.06	0.04	0.07	0.02
18	0.03	0.08	0.41	0.25	0.74	0.37	0.14	0.14	0.07	0.05	0.05
19	0.02	0.10	0.30	0.18	0.19	0.06	0.08	0.09	0.04	0.05	<b>1.00</b>
20	0.05	0.20	0.66	0.28	0.48	0.35	0.13	0.15	0.11	0.08	0.11
21	0.05	0.13	0.59	0.30	0.49	0.24	0.15	0.10	0.08	0.09	0.25
22	0.06	0.18	0.75	0.28	0.40	0.39	0.17	0.10	0.07	0.13	0.16
23	0.05	0.15	0.49	0.19	0.30	0.22	0.13	0.30	0.11	0.12	0.19
24	0.00	0.03	0.06	0.02	0.03	0.02	0.04	<b>1.00</b>	0.04	0.00	0.04
25	0.00	0.05	0.01	0.00	0.02	0.00	0.02	0.99	0.10	0.00	0.09
26	0.02	0.10	0.34	0.08	0.16	0.15	0.12	0.59	0.18	0.04	0.19
27	0.02	0.05	0.24	0.08	0.16	0.12	0.12	0.44	0.20	0.03	0.50
28	0.03	0.06	0.28	0.13	0.12	0.33	0.05	0.42	<b>1.00</b>	0.05	0.16
29	0.01	0.13	0.20	0.11	0.14	0.49	0.10	0.62	0.27	0.03	0.09
30	0.03	0.12	0.35	0.12	0.20	0.27	0.15	0.52	0.16	0.07	0.13

note1: In the vertical column represents occupations: (1) senior management occupations (2) specialized middle management (3) middle management occupations in retail and wholesale trade and customer service (4) middle management occupations in trades, transportation,

production and utilities (5) professional occupations in business and finance (6) Administrative and financial supervisors and administrative occupations (7) finance, insurance, distribution, tracking, scheduling and related business administrative occupations (8) office support occupations (9) professional occupations in natural and applied sciences (10) technical occupations related to natural and applied sciences (11) professional occupations in health (including nursing) (12) technical and assisting occupations in health (13) professional occupations in education services (14) professional occupations in law and social, community and government services (15)paraprofessional occupations in legal, social, community and education services (16) public protection, care providers, educational, legal and protection support occupations (17) professional and technical occupations in arts, culture, recreation and sport (18) retail sales supervisors and specialized sales occupations (19) service supervisors and specialized service occupations (20) sales representatives and salespersons (21) service representatives and other customer and personal service occupations (22) sales support occupations (23) service support and other service occupation (24) industrial, electrical and construction trades (25) maintenance and equipment operation trades (26) trade helpers, construction labourers, installers, repairers and related occupations (27) transport and heavy equipment operation and related maintenance occupations (28) supervisors, technical occupations and workers in natural resources, agriculture and related production (29) supervisors and operators in processing, manufacturing and utilities (30) Assemblers and labourers in processing, manufacturing and utilities.

Note 2: In the horizontal row represents field of study: (1) education (2) visual and performing arts, and communications technologies (3) humanities (4) social and behavioral sciences and law (5) business, management and public administration (6) physical and life sciences and technologies (7) mathematics, computer and information sciences (8) Architecture, engineering and related technologies (9) agriculture, natural resources and conservation (10) health and related fields (11) personal, protective and transportation services

The purposes of the article concentrate on the match between the occupation and field of study for individuals; hence, Table 1 reveals the partial results of the distribution of field of study to occupational match ratio, which are included, and only nine out of thirty occupations shown above actually have a match ratio of 1. After differentiating the most associated occupations with ten different field of studies from the thirty occupations, the next step in my study was to classify the degree of computerization in the nine most related occupations. The approach I took to finding which occupations most related to an individual's field of study were facing high or low degrees of computerization was referencing Frey and Osborne's novel methodology for categorizing jobs based on occupational characteristics and their susceptibility to computerization by examining the jobs' future directions and how the labor market should cope with all technological changes. The two economists assigned each job in the O\*NET database with a probability of being automated by evaluating the occupation's creativity, social intelligence, perception, and manipulation. FO listed 903 specific occupations and used their knowledge to rank 702 jobs. However, the NOC11 simply provides 30 different broad occupations in the 2011 Census, which means I was unable to create cross references in

my study. By carefully studying how to decide the probability of computerization for different occupations in FO's study, I thus measured the level of computerization for the 30 broad jobs by applying Frey and Osborne's evaluative methods (Frey and Osborne, 2013).

A relatedness equal to 1 indicates the field of study and occupation is perfectly matched, which means the majority of each major had the single most related occupation. Furthermore, to discover the computerization level for the perfectly matched individuals, I followed Frey and Osborne's novel methodology by sorting the computerization into three level, which are 1 (low computerization), 2 (medium computerization), and 3 (high computerization). The professional occupations with low computerization were the type of jobs with a high degree of education and high knowledge in their area of study that cannot be replaced by automation at this moment.

### **Regression analysis**

In the regression analysis, the relatedness between an individual's occupational mismatch and the level of computerization was explored in-depth. There were two noticeable situations in the regression analysis. First, I generated a new variable NRI to classify the normalized RI into two class intervals (1.0-0.80, 0.80-0.00). The NRI was equal to 1 if the normalized RI was greater than 0.80, which means the occupation and field of study were a match; or the NRI was equal to 0 if the normalized RI was less than 0.80, which indicates a mismatch between the occupation and field of study. Then, I identified the occupations most related to the workers' field of studies (NRI equal to 1)



that also have a higher computerization risk, because the higher computerization risks are, the more the workers' trained occupation would determine the workers' occupational mismatch.

The table 2 shows the selected variables in the OLS analysis. The correlation between occupational match and higher computerization risk are interesting. The medium computerization risk occupations have a negative relationship with the match between the workers' field of study and train occupation. However, we cannot observe the same relationship for the high computerization occupations.

The results presented in Table 2 indicate that a worker whose field of study has a higher level of computerization risk would have a 21.45% higher probability of an occupation to field of study mismatch on average. This illustrates how occupations with medium automation risk are the most proven to have the highest risk of occupational mismatches. In my regression analysis, there were two medium risk occupations among the nine categories in NOC11 that matched with the ten field of studies in the CIP2011. Through careful study of the two medium risk occupations categorized by NOC11 in the Statistic Canada, the detailed jobs with medium automation risks were supervisors and technical workers who work in natural resources, agriculture, and related production, service supervisors, and some particular service workers. This also indicates that the students who major in natural resources, agriculture, personal protective study, and transportation will find it difficult to find a job that matches with their field of study.

Table2: OLS estimates of computerization —2011

Variable	Coef.	(Std. Err)
----------	-------	------------

SEX			
Male		-0.0164***	(0.0021789)
AGEGRP			
20 to 24 years		0.1057***	(0.0115852)
25 to 29 years		0.1974 ***	(0.0113887)
30 to 34 years		0.1836 ***	(0.0113383)
35 to 39 years		0.1643 ***	(0.0113209)
40 to 44 years		0.1365***	(0.0112941)
45 to 49 years		0.1308 ***	(0.0112620)
50 to 54 years		0.1378***	(0.0112925)
55 to 59 years		0.1372***	(0.0113962)
60 to 64 years		0.1317 ***	(0.0117236)
PR			
Prince Edward Island		-0.0420**	(0.0185428)
Nova Scotia		-0.0190*	(0.0110950)
New Brunswick		-0.0025	(0.0116921)
Quebec		-0.0346***	(0.0093383)
Ontario		-0.0554***	(0.0092652)
Manitoba		-0.0003	(0.0110069)
Saskatchewan		0.0064	(0.0112736)
Alberta		-0.0298**	(0.0096013)
British Columbia		-0.0268**	(0.0095748)
Northern Canada		0.0740**	(0.0305376)
occcom			
	2	-0.2145***	(0.0043566)
	3	0.0220***	(0.0026765)
Constant		0.1996 ***	(0.0142608)
R^2			0.0107
F			170.92
N			209,685
*p<0.1, **p<0.05, ***p<0.01			

Nevertheless, the occupational mismatch for the workers who work in occupations with high computerization risk declined 2.2 percent. Apparently, the result was contrary to what we had expected, because it indicates the individuals who work in high risk automation jobs related to their field of study would not be compelled to leave their workplace due to automation. The only occupations at high risk of computerization

among the nine occupations matched with the field of studies was industrial, electrical, and construction workers.

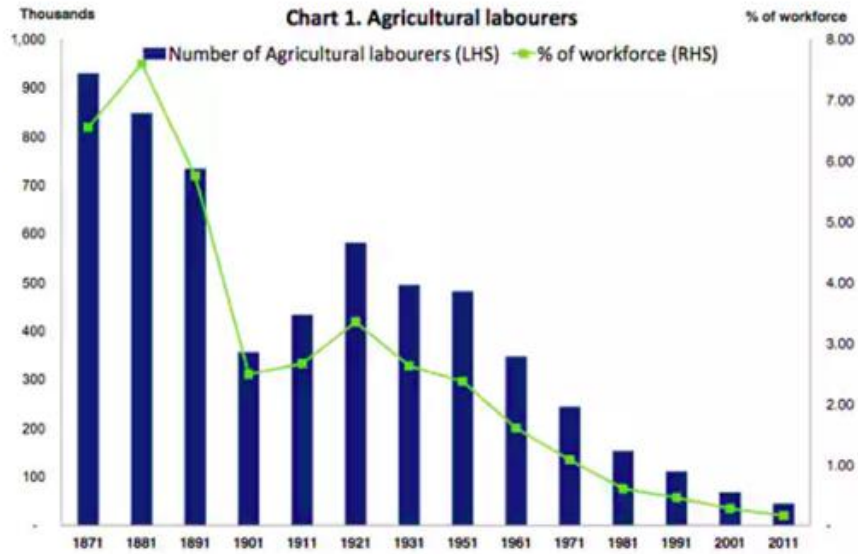
FO expected humans have the comparative advantages of perception and manipulation at medium risk occupations is temporary; nonetheless, the development of technology will eventually eliminate the understanding and manipulation gap between human and robots. In addition, Arntz, Gregory, and Zierahn (2016) mentioned the method that Frey and Osborne used to standardize occupational computerization risk was flawed because for some professions that FO expected to experience high automation risk, they are hard to automate, such as jobs that require interactions and communication with people. Arntz, Gregory, and Zierahn (2016) pointed out that FO believe people who are facing an extremely high automation risk of 98% are employed in occupations such as bookkeepers, accountants, and auditing clerks, but 74% of the total employment need high levels of interactivity and group work with their colleagues that cannot be displaced by machines. Moreover, the retail salesperson is listed as a high-risk occupation in FO's calculation, yet the results of the Princeton Data Improvement Initiative show that only 4% of retail salespeople work with no teamwork or interactions.

### **Examination of the impact of technological developments on employment**

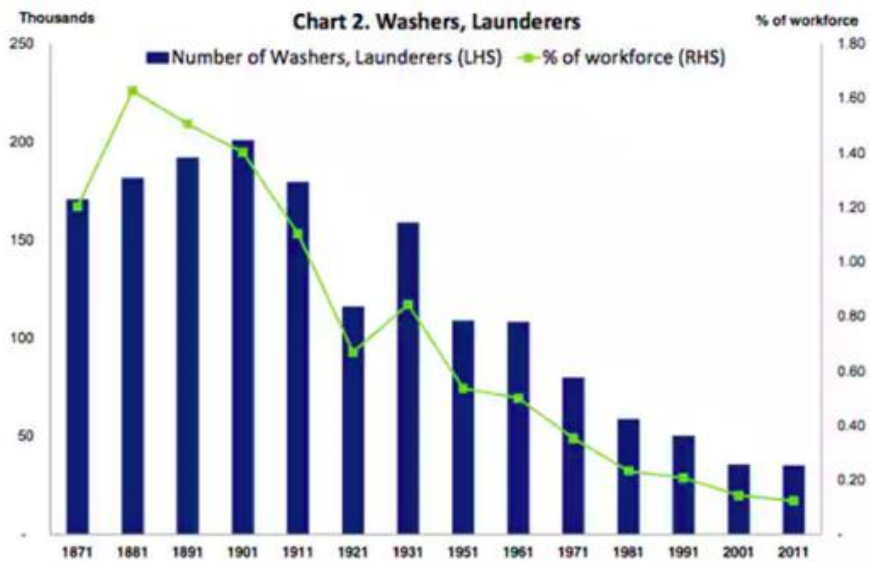
Technical corporations have innovated many advanced machines with the positive motivation of developing efficiency. Meanwhile, this motivation is of concern to the public because it could negatively impact labor demand especially for workers. In the information technology era, globalization and new technological advances are

transforming the employment structure and nature of work. Numerous manual and routine tasks have been automated because of the increase in computerization power. The rise of emerging technology has already diminished the job demand for unskilled workers, with only a few number of low paid jobs for middle skilled workers and an increasing demand for highly skilled people. Job polarization between unskilled workers and highly skilled workers has worsened due to a large number of middle class workers suffering from unemployment while highly skilled workers are earning more in the IT era. A new type of unemployment has already formed, which is called technological unemployment.

Technological growth has replaced a lot of physical works and has led to significant labor force switching because many manual jobs become unnecessary, which forces the low-skilled workers to evacuate. Machines can substitute a lot of manual occupations if the rise in advanced technology is further improved. Humans have invented new technologies that can replace most of the jobs handled by unskilled individuals.



Source: Katie Allen (2015) Technology has created more jobs than it has destroyed. Using census data

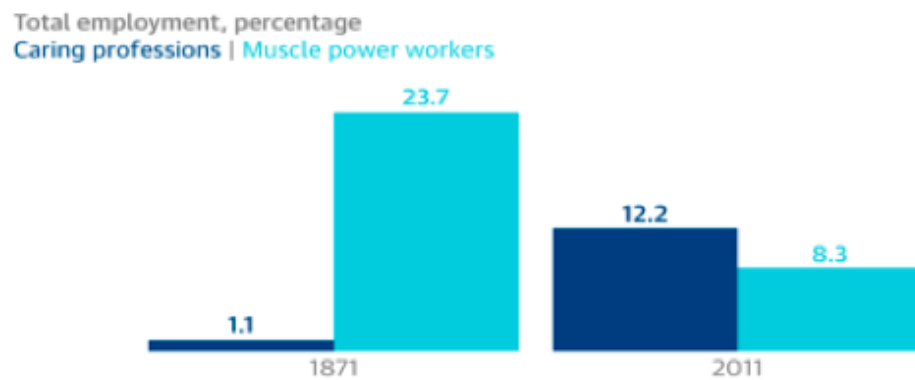


Source: Katie Allen (2015) Technology has created more jobs than it has destroyed. Using census data

Both charts shown above represent the percentage of the workforce and how the demand for agricultural labors, hand washers, and launders has changed in the last 140 years in England. This data was collected from England and Wales Census. Diagram 1 indicates the labor demand in the agriculture area. Allen (2015) believes that agriculture is a sector that would most likely suffer the

impact of the rapid technological development as it directly influences farm occupations.

Technology will improve productivity and substitute unskilled employees. The number of farming labors had reduced from 950,000 in 1871 to only around 30,000 in 2011. In chart two, the census data shows that jobs that were once-popular have suddenly declined in their popularity because of technological development; such jobs include washers and launderers. The demand for these labors once went up to 200,000 in 1901, but it has declined to 40,000 in 2011. The overall tendency of both charts indicates a declining trend from 1871 to 2011 considering the growth in technological innovations.



Note: 'Muscle power workers' includes cleaners, domestic servants, labourers and miners. 'Caring professions' include health and teaching professionals and care home workers.

Source: Katie Allen (2015) Technology has created more jobs than it has destroyed. Using England and Wales Census data

The chart above represents the fact that Allen (2015) introduced a graph called "Labor Switching" by collecting data from the England and Wales Census records, which indicates a significant labor switching from muscle power workers to caring professions from 1871 to 2011. People are aware of the decline in manual work opportunities, and they need to understand the trend and make an effective change in their field of study.

Furthermore, the data collected from Statistics Canada describes the percentage of the change in employment type between 2015 and 2016. It mentions that jobs in agriculture have recorded total losses of 19,000 in 2016, which is a 6.2% fall in one year. About 11,000 less people are working in the manufacturing area in 2016, compared to 2015. Employment in transportation and warehousing has decreased by 10,000. Statistics Canada data shows that traditional jobs are gradually disappearing.

Technology development has greatly contributed to boom production and reduced labor costs for various industries. However, Beauday, *et al.* recorded that the demand for skilled workers has continuously declined for the last ten years, but the supply of highly educated employees has continued to grow. Beauday, *et al.* indicated that highly skilled and educated workers have to find less work than expected and take positions that used to belong to relatively low skilled workers, further pushing the lower level skilled workers down or even out of the labor force. The unemployed workers who were dismissed due to new technologies can be considered to be those suffering from technological unemployment.

## **Conclusion**

Presently, artificial intelligence is a hot topic in developed countries, and there are different opinions about it. Some believe that robotics, machine learning and advanced automation will significantly improve the economy and the whole society. However, some other people fear that the rapid growth of advanced technology will bring about an existential threat to humanity. This paper has investigated the degrees of jobs' computerization risk which were analyzed by Frey and Osborne's (2013) study and related this to how this computerization risk affects the workers' field of study and how it

causes occupation mismatch, using the data from 2011 National Household Survey in Canada. The results show that workers who have a degree in the specific field of study and take medium computerization risk occupations would have 21.45% occupation mismatch tendencies. However, the workers who take a field of study related to high computerization occupations would decrease their mismatch rate by 2.2% and this is extremely minute. This indicates that workers who take medium risk jobs have the largest mismatch rate; these fields of study are mainly centered on natural resources, production and agriculture. Besides, the occupations with highest automation risk such as industrial, electrical, and construction workers will assuredly have mismatch issues.

Nevertheless, this paper has proven that automation has the competency to cause field of study and occupation to mismatch. However, the question is: what is the future of the unemployed and mismatched workers that were displaced by machines? Individuals with an optimistic attitude will decide to continue expanding their educational goals in order to be employable; but there are many relative tough problems such as the workers' age, the difficulty for low-income level workers to afford tuition, and the workers' competence and intelligence. There is an uncertain conclusion and prospect about how emerging technology will take over jobs. However, the impact of the technology's growth on unskilled workers is obvious.



## Reference

- Allen, K. (2015). "Technology has created more jobs than it destroyed, says 140 years of data." *The Guardian*, August 2015. Retrieved from <http://www.theguardian.com/business/2015/aug/17/technology-created-more-jobs-than-destroyed-140-years-data-census>.
- Arntz, M., T. Gregory and U. Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: vA Comparative Analysis", *OECD Social, Employment and Migration Working Papers*, No. 189, OECD Publishing, Paris.
- Beaudry, P., Green, D.A. and Sand, B.M. (2013). The great reversal in the demand for skill and cognitive tasks. Tech. Rep., NBER Working Paper 18901, National Bureau of Economic Research.
- Darcy Hango "Gender difference in sciences in science, technology, engineering, mathematics and computer science (STEM) programs at university" *Statistic Canada*. Retrieved from <https://www.statcan.gc.ca/pub/75-006-x/2013001/article/11874-eng.htm#a4>
- Frey, C.B. and M.A. Osborne (2013), *The Future of Employment: How Susceptible are Jobs to Computerization?*, University of Oxford.
- Ghaggarzadegan, N., Xue, Y. & C. Larson, R. (2017). "Work-education mismatch: An endogenous theory of professionalization." *European Journal of Operational Research*, 261 (2017) 1085-1097
- Moore, G. E. (1965) Cramming more components onto integrated circuits. *Electronics*, 38, 114-117.
- Te Riele, K. & Crump, S. (2003). Ongoing inequality in a "knowledge economy": Perceptions and actions. *International Studies in Sociology of Education*, 13(1), 55-76.
- Statistics Canada. (2001) *Education Quarterly Review* (vol.7. no. 02). Retrieved from <http://www.statcan.gc.ca/pub/81-003-x/81-003-x2000002-eng.pdf>
- Statistics Canada. (2011). 2011 National Household Survey public use microdata file (PUMF): Individuals file. Catalogue no. 99M0001. Retrieved from <http://www62.statcan.ca.library.smu.ca:2048/webview/pdf?&mode=ddiToPDF&executepdf=true&study=http://142.206.64.59:80/obj/fStudy/NHS-99M0001-E-2011-Individuals&s=&gs=&language=>