Evaluating the Future of Skills, Jobs, and Policies for the Post COVID Digital Economy

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Michelle Alexopoulos
University of Toronto
malex@chass.utoronto.ca

Kelly Lyons*
University of Toronto
*Corresponding author: kelly.lyons@utoronto.ca

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Executive summary

Background: the issue

Data science provides methods to understand and solve problems in an evidence-based manner by combining data and experience, with scientific methods. When combined with advances in robotic technologies, telecommunication technologies and internet coverage (digitally enabling infrastructure), and computer hardware, data science creates a host of "digital technologies" expected to bring value to business, government, and individuals. This potential has been rising, in part, because of access to growing amounts of data from business applications that can be used in conjunction with the expanding set of digital innovations across a wide array of applications.

The adoption of the digital technologies by firms across large components of the Canadian economy has the potential to create disruption in the labour market in the form of technological unemployment, labour and skill shortages in rapidly growing sectors and the potential transformation of skill requirements for existing occupations. To add to the increased uncertainty, the onset of the COVID-19 pandemic has introduced previously unforeseen challenges to the adoption and further development of digital technologies, potentially altering the speed of diffusion and pace of technical change and the transition to the digital economy for organizations and workers. The lack of real-time data to track the impact that COVID-19 has had on: (1) the rates of digital technology innovation, (2) the speed of adoption and diffusion of current digital technologies among Canadian firms, and (3) the disruption to difference groups of workers, has created significant gaps in knowledge for organizations and policy makers alike.

Objectives

The objective of our knowledge synthesis project is to help fill part of the knowledge gap by providing broad-based evidence on the shifting landscape for organizations and workers with a main focus on: (1) uncovering trends on how digital technologies were transforming the nature of work in different sectors pre-COVID-19, and identifying what impact, if any, has COVID-19 has on innovation and adoption of these key technologies, (2) reviewing evidence on skill gaps and labour market challenges that have been identified by Canadian organizations and in research, and (3) highlighting policies and programs that can help maintain a skilled workforce that can meet evolving labour demand and work to ensure that all Canadians benefit from the transition to the digital economy.

Methodology

To achieve our objectives, we drew on a mix of text-based and non-text-based sources of data and used a multi-faceted, mixed-methods approach to analyse data and synthesize findings. The breadth of methods was necessary to enable us to comment on the rapidly changing environment in the face of both technical change and the pandemic given that the time lags associated with official data releases are often considerable. Given our desire to document both the recent pre-pandemic trends, as well as the trends after the onset of COVID-19, we primarily focused on statistics and textual materials from the period 2015-April 2021 whenever possible. Official data from Statistics Canada on R&D and business investment were examined, along with data on Canadian and US patent filings, and Canadian grant applications. Since these data did not fully allow us to derive a comprehensive picture of adoption and innovation of digital technologies both pre-and post COVID-19, we expanded our collection of data to include data on robot installations and forecasted installations from the International Federation of Robotics (IFR), job posting data (available from Labour Market Information Council - LMIC), as well as data on downloads of Python machine learning packages and search trends for machine learning packages.

The data collected was then supplemented with information gleaned from a systematic literature review and distance reading methods applied to a variety of peer-reviewed publications and related grey literature. For our systematic literature review we used the platforms Engineering Village (EV), ProQuest, EBSCOHost, Scopus, and Web of Science (WoS) to identify journal articles and conference publications meeting the criteria. Distance read methods were also applied to the systematic literature review corpus as well as to papers dealing with digital technologies and labour market issues that were collected from Canadian think tanks and major consulting firms to gain additional insights into patterns of adoption and diffusion across countries and sectors. These findings were then complemented with trends seen in the number of newspaper articles covering digital technologies in Canada and abroad, as well as general trends in journal publications related to the AI, data science and robotic technologies indexed in EV and WoS, and current job titles from LinkedIn.

Results

Taken as a whole, the available evidence indicates that, prior to the pandemic, the commercialization and diffusion of AI, data science and robotic related technologies was growing at a rapid pace. However, with the onset of the pandemic, the lockdowns and restrictions caused a severe recession that appears to have delayed investment and adoption plans for these technologies for many firms in the economy, and slowed the pace of related innovation in these areas.

The slowdown in commercialization and innovation likely means that the timing of labour market disruptions and the possible emergence of skill gaps related to the adoption of the associated technologies for the majority of sectors will occur at least a few years later than forecasts made prior to the pandemic would suggest. However, if the trends seen since December 2020 continue, and future COVID-19 waves do not force additional closures or severe economic disruption, these data would suggest that employment opportunities related to AI and data science will quickly surpass their pre-pandemic levels and usher in increased productivity growth.

As is the case with all technical change, there is a concern that many jobs could be lost or transformed, and that certain workers will be displaced as a result while firms face shortages of skilled labour in other areas. The magnitude of the disruption, however, is still a source of disagreement. The most recent forecasts for Canada produced by Wyonch (2020) concluded that the only about 22% of Canadian Jobs are currently at high risk of automation over the next few decades while Frenette and Frank (2020) estimated that job transformation risk is at least 10% for 98.2% of the paid workforce with only 10.6% if workers facing a high risk of 70% or more. Interestingly neither study found significant disparities in risk related to gender, or disabilities. Instead, the risk was estimated to be larger for younger and older workers (18-24 and 55+), workers in occupations with a higher share of routine tasks associated with them, and for individuals with lower levels of educational attainment.

Key messages

There is already evidence that demand for workers in areas related to computer science, computer software, and mechanical engineering is rapidly expanding, and the share of the Canadian economy impacted by digital technologies will continue to expand even if the pace overall has been impacted in the short run by the pandemic.

Well-designed policies and interventions can help smooth the transition for firms and workers alike with future policies encouraging upskilling, and retraining of workers, as well as promoting the acquisition of skills in high demand though micro-credential programs, co-ops or internships, and post-secondary education. Additional peer-reviewed research should also be undertaken to ascertain the effectiveness of basic income supports for displaced workers and targeted support for business investment and R&D programs to increase innovation, economic growth and international competitiveness.

Given the identified shortcomings of available data, more emphasis should be placed on encouraging the development of high-quality data that can used by researchers and policy makers to better track the evolving trends and assess the need for labour market intervention and support for Canadian firms and workers.

Full Report

1. Background

Data science provides methods to understand and solve problems in an evidence-based manner by combining data and experience, with scientific methods. When combined with advances in robotic technologies, telecommunication technologies and internet coverage (digitally enabling infrastructure), and computer hardware, data science creates a host of digital technologies expected to bring value to business, government, and individuals. This potential has been rising, in part, because of access to growing amounts of data from business applications, sensors, and individuals and the availability of numerous and diverse off-the-shelf artificial intelligence (AI), fintech, and data analytics tools, many accessible through virtualized cloud-based computational resources. In 2017, companies' data asset volume was found to be growing an average 40% per year [31]. Recent studies [15, 21] confirm that mastering big data affords strategic advantages to corporate users, and that early adopters of the most advanced analytics capabilities outperform their competitors. As technologies around digital platforms evolve and mature, the opportunities for local, national and international economies will increase. Some pre-pandemic predictions suggest AI could contribute up to $15.7T to the global economy in 2030 [27]. This is partly because AI is creating new industries and lowering barriers to participation and access [13]. The onset of the pandemic has introduced previously unforeseen challenges to the adoption and further development of digital technologies- potentially altering the speed of diffusion and pace of technical change thereby altering the transition to the digital economy for organizations and workers.

2. Objectives

The lack of real-time data to track the impact that COVID-19 has had on the transition to the digital economy has created significant gaps in knowledge for organizations and policy makers alike. The objective of our knowledge synthesis project is to fill this gap by providing: (1) clearer broad-based evidence on the shifting landscape for organizations and workers, (2) evidence about pre-COVID-19 and current predictions for future skill requirements, and the digital technologies' effects on the future path of job creation and disruption, and (3) a review of policies that may help smooth the transition for workers and organizations. Specifically, the report will address the following questions. First, how were digital technologies transforming the nature of work in different sectors pre-COVID-19, and what impact, if any, has COVID-19 had on innovation and adoption? Second, what skill gaps and labour market challenges have been identified by Canadian organizations and research, and how are employers, educators and policy makers supporting the creation of a skilled workforce that can meet evolving labour demands? Third, what policies and programs can be adopted to ensure that all Canadians benefit from economic growth in the digital economy? We will address these questions in the sections below in the context of three interrelated themes over the period 2015 to present. The first theme discusses the shifting landscape for firms and workers by uncovering evidence on the trends in the adoption and diffusion of AI and data science related technologies in Canada pre- and post-COVID 19. The second theme focuses on the effects of technological change on the labour market to undercover recent changes in employment opportunities, skill gaps, job loss and to help document views on the future path of Canadian labour demand and supply as Canada transitions to a more digital economy. The third theme highlights policies that have been identified in the literature that may assist Canadian firms' ability to compete internationally, promote wide-spread economic growth in Canada, support the evolving labour needs of firms over future years and to help displaced workers transition to a new economy. The first two themes are discussed in section 4 and the last theme is discussed in detail in Section 5.

3. Methods

To answer our research questions, we drew on a mix of text-based and non-text-based sources of data and used a multi-faceted, mixed-methods approach to analyse data and synthesize findings. The breadth of methods was necessary to enable us to comment on the rapidly changing environment in the face of both technical change and the pandemic given that the time lags associated with official data releases are often considerable. Below, we begin by: (1) describing the various text and non-text-based data sources we used and (2) outlining the methods and approaches taken with each data source. We also briefly describe how the analyses and data sources contributed to various aspects of our findings for each of our three themes.

3.1 Text-Based Data Sources and Methods

We gathered text data from several sources and applied a variety of quantitative analyses on these data as well as a close reading qualitative analysis. The list of sources is given below followed by the methods and approaches used to analyse the data.

3.1.1 Text Based Data Sources and Keyword Queries:

Publication Databases: The platforms we used to search and retrieve publications for the systematic literature review were Engineering Village (EV), ProQuest, EBSCOHost, Scopus, and Web of Science (WoS). A full list of the databases consulted for the systematic literature review in each platform can be viewed in Appendix A.2. We also gathered data about journal and conference publications related to AI and data science from 2010 to 2020 and focused on items indexed in EV (which provides access to twelve engineering document databases that include journals, conference proceedings, trade publications, patents, and government reports) and the WoS Science Citation Index Expanded and Conference Proceedings Citation Index databases. The text of the EV and WoS basic searches are provided in Appendix B.

Think Tank & Consulting Reports: We identified a list of consulting firms and a list of Canadian think tanks from which to gather reports. We used the list of consulting firms identified as the top 25 by Statista in 2020[1] and further included their Canadian sites, if available. The Canadian Think Tanks were selected from the Canadian Think Tank Guide by McGill University[2] and US Think Tanks were identified from the Harvard University Library and Knowledge Services Think Tank Search[3]. The full list of the 41 selected consulting firms (16 of which are Canadian arms of the firms) and the 38 Canadian Think Tanks is in Appendix E.

Newspaper Database (Factiva): Newspaper articles tied to AI, data science and robotics are useful in discerning the level of interest in these digital tools and techniques in industries and businesses [2]. We counted the number of articles that mention AI- and data science-related terms from all English language newspapers in Factiva for each year from 2010 to 2020, and also counted the number of monthly mentions of those terms for US and Canadian newspapers from January 2020 to May 2021. The terms used for the searches are found in Appendix D.

Keywords Everywhere data: We used a tool called Keywords Everywhere[4] that combines data from *Microsoft Bing*, *Google Trends*, other sites, and some of Google's additional database information such as Keyword Planner to retrieve raw search volumes for queries related to machine learning (ML) tools. Raw volume data was used since it is easier to compare searches (and, hence, interest in topics) over time due to the fact that the data is not normalized by the volume of other searches in the region during the period (as is the case with *Google Trends*[5]). Monthly Google and Bing search volume data (worldwide and Canada-specific) was collected and compared for popular ML Python package names [10, 26, 28] from April 2017 to April 2021 (Appendix C lists the search terms considered; the data was downloaded between April 10 and 15, 2021).

1. https://www.statista.com/statistics/190343/25-leading-us-consulting-firms-by-overall-prestige-2011/
2. https://www.mcgill.ca/caps/files/caps/guide_canadianthinktanks.pdf
3. https://guides.library.harvard.edu/hks/think_tank_search/US
4. https://8https//keywordseverywhere.com/
5. https://support.google.com/trends/answer/4365533?hl=en

LinkedIn Job Titles: Existing data on the occurrence of the term "data scientist" appearing in the *current job title* field in LinkedIn were merged at discrete points in time from June 2017–April 2021 to determine trends.

Funding Awards Databases (SSHRC, NSERC): We queried the NSERC Awards Database[6] and the SSHRC Award Database[7] for the fiscal years 2015-2016 to 2019-2020 (data for 2020-2021 was not available at the time of this study) searching for data-science related terms in the keywords and summary for NSERC and in titles and keywords for SSHRC for all award types (the full list of keywords is in Appendix G). We then identified the total amount and proportion of funding invested in data science related projects year-over-year for both NSERC and SSHRC.

3.1.2 Other Text Based Methods

In addition to the keyword search methods described above, we conducted a systematic literature review, analysed publications related to AI and data science, and carried out distant readings. These require more detailed explanations which are presented in this section.

3.1.2.1 Systematic Literature Review

The steps in conducting the systematic literature review were inspired by elements of the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA–P) 2015 checklist and the Cochrane Review—a systematic review method used in the health science discipline which gathers empirical evidence by applying predetermined eligibility criteria to answer specific research questions [30]. In contrast to traditional literature or narrative reviews, the Cochrane Review has an explicit search strategy, inclusion and exclusion criteria, and a clear process for selecting articles. The justification for choosing the Cochrane Review as a reference is that it has helped achieve a greater degree of transparency, rigour, and comprehensiveness when analyzing the chosen body of literature (i.e., scholarly and grey literature). We used a combination of close reading and distant reading techniques to identify the final list of articles.

Eligibility Criteria: The main concepts that were used to develop the eligibility criteria include digital technologies, the nature of work, transformation (innovation and adoption), publication type, and language. Descriptions for each concept are provided below (details about the eligibility criteria are given in the screening guidance tables in Appendix A.1).

> **Digital Technologies:** Publications focused on digital technologies relating to artificial intelligence and data science, such as machine learning, neural networks, predictive analytics, and algorithms were included. Publications that describe analog technologies such as tape players, record players, and photocopiers were excluded.
>
> **The Nature of Work:** Publications that discussed the nature of work, changes to the labour market, and industry employment were included (e.g., employment, unemployment, jobs, and labour), whereas those that examined digital technologies unrelated to work were excluded (e.g., leisure, volunteering, unpaid internships, and personal projects). Publications that did not describe a change in the nature of work, for instance, those that concentrated on job descriptions, were also excluded.
>
> **Transformation:** Transformation focuses on the innovation and adoption of digital technologies. Publications discussing forecasting for industry trends and individual firms were included, unlike publications that did not examine changes, investments, future forecasting, or predictions.
>
> **Publication Type:** Publications published between 2015–2021 were obtained from various grey literature and scholarly databases in text format. Multimedia (e.g., videos, audio recordings, social media, personal blogs, magazines, and encyclopedias) and articles published prior to 2015 were excluded.
>
> **Language:** Only publications in English were included.

6. https://www.nserc-crsng.gc.ca/ase-oro/index_eng.asp
7. https://www.sshrc-crsh.gc.ca/results-resultats/award_search-recherche_attributions/index-eng.aspx

Information Sources: The platforms used to search and retrieve publications were Engineering Village, ProQuest, EBSCOHost, Scopus, and Web of Science. A full list of the databases consulted in each platform can be viewed in Appendix A.2.

Search Process: A search strategy was developed on the Engineering Village platform which was then adapted to the other four platforms. A list of keywords was determined following a series of brainstorming sessions with the review team. These keywords were constructed into search strings. The resulting search strategy was tested in Engineering Village and used to interpolate a list of subject headings. These subject headings informed revisions to the initial search and the searches were then translated to ProQuest, EBSCOHost, Scopus, and Web of Science. The search strategies and the date of retrieval can be viewed in Appendix A.3

Publication results with titles and abstracts, as well as appropriate metadata such as publication year, main/subject headings, author keywords, and index keywords were exported to Excel from each of the five databases. A programmatic filtering step was applied to the output of all five databases, yielding the final list of publications to be screened.

Filtering Step: A script written in Python was used to assign weights to keywords in the abstracts and titles of the dataset. The weights were determined by the review team. In general, work-related keywords were weighted more heavily than technology-related keywords. The keywords to be excluded were assigned a score of −1. The list of keywords was derived from the eligibility criteria (Appendix A.1) with adjustments based on discussions with the review team and observations of keywords that captured the essence of the research questions. The keywords and their weights are listed in Appendix A.4.

We applied a seven-step filtering process for each of the retrieved titles and abstracts to generate an overall score for each publication. These steps are presented below with examples given in Appendix A.5. Articles with an overall score of 3 or above were included in the next step (the screening process) and the rest of the articles were not included.

Step 1: Keyword(s) in abstract: The first step was to check if the abstract contained keywords that could be classified as both technology-related and work-related.

Step 2: Calculated overall score based on abstract: Then, we calculated a score based on the presence of keywords in the abstract. For example, if a keyword appeared multiple times in the abstract, a maximum of three occurrences were considered.

Step 3: Calculated overall score based on title: If a work-related keyword was found in the title, its weight was doubled.

Step 4: Classification codes: If a paper's classification codes contained the term "labour," (or "labor") another 4 points were added to the overall score.

Step 5: Main headings: If a paper's main heading (in the classification code) was "economic and social effects", "employment", or "personnel training" another 4 points were added to the overall score.

Step 6: Additional keywords from abstract: If an abstract had 5 or more matched keywords, each of its keyword's weight was counted again in the overall score. In each of the following situations, the overall scores were reduced by half to account for the relevance for both the technology-related and work-related keywords: If an abstract contained only 2 technology-related keywords, or if an abstract had only 1 work-related keyword

Step 7: Industry relevance: In the last step, to be as inclusive as possible for all industries, if a paper's classification codes contained a specific industry the score was reduced to a quarter of the overall score. The list of the industries for reduced scores include the following: building, bridge, tunnel, agricultur*, construction, roads, coastal, meteorology, atmosphere, water, air, waste, ecosystem, bio, geology, mineral, soil, seismology, mining, oil, gas, heat, space, railway, storage, chemical, solar, beverage, footwear, automotive, metallurgic, and goods distribution.

Screening using Covidence: The resulting list after the filtering step was used to select the publications for screening. These publications were uploaded to Covidence[8] , a web-based service that streamlines the screening and data extraction process for systematic reviews. A team of five research assistants completed the title and abstract screening and data extraction phases using Covidence. A single reviewer method was set for both screening and data extraction stages using the form in Appendix A.6.

A total of 797 publications were imported into Covidence with 161 duplicates removed by the software, leaving 636 which were screened for title and abstract based on the eligibility criteria, resulting in 278 articles included in the data extraction phase (See Figure 1).

Citation network analysis: After performing data extraction, we conducted a citation network analysis of the publications to identify any relevant and highly cited publications by authors working in this area that were missed. This strategy was used to overcome the limitations of the search strategy focused on keywords and the time lag in the databases. We used CERMINE [35], a Java library for PDF content extraction, to extract the references information in each paper. We then identified the papers that are referenced more than three times for further investigation. A total of 164 articles were identified by the citation network analysis and screened for title and abstract eligibility which resulted in a total of 61 articles that were imported to Covidence. After conducting full-text screening, 41 articles were included in the data extraction phase (20 were excluded for having an irrelevant topic or the wrong publication type).

A total of 319 articles were collected and analyzed in the literature review (see Appendix I for the list of articles). The flowchart of this process can be viewed in Figure 1.

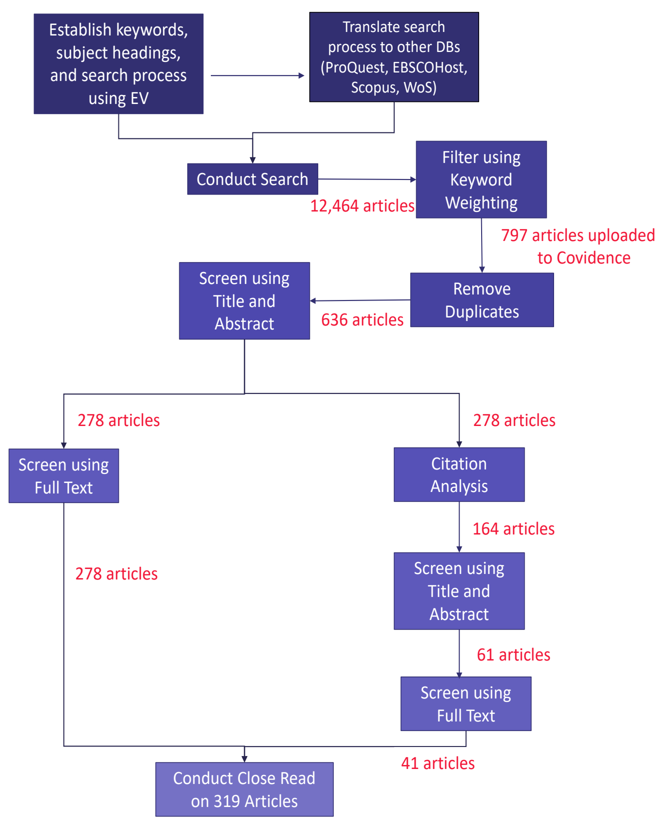


Figure 1: Flowchart showing systematic literature review methodology.

8. https://www.covidence.org/

3.1.2.2 Analysis of publications related to AI and Data Science:

We compared the number of data science related articles (see Appendix B for the list of keywords used) from EV and WoS year-over-year from 2010 to 2020 to uncover publication trends in the area. Engineering Village (EV) provides access to twelve engineering document databases that include journals, conference proceedings, trade publications, patents, and government reports. Web of Science (WoS) has Science Citation Index Expanded (SCI-EXPANDED)[9] and Conference Proceedings Citation Index-Science (CPCI-S)[10] databases. We also analysed country affiliation of authors for each paper. Since a paper can be authored by researchers in multiple jurisdictions, two sets of regional breakdowns were created. In the first case, a paper was included in the country's count if there existed at least one author identified as being at an institution in that country. In the second case, a paper was included in a country's count only if all authors were identified as being in an institution in that country. The rationale for examining these two cases relates to the notion that having some co-authors outside your country may provide a type of insurance on disruption since other members of the team in other jurisdictions may be able to work and pick up slack if one member is unable to work temporarily due to restrictions, family care responsibilities associated with school closures, illness, etc. We compared publication patterns by authors from Canada, China, the US, and the UK.

3.1.2.3 Distant Reading Methods

In addition to the 319 articles identified through the systematic literature review, we gathered two additional corpuses of documents sourced from global consulting firm reports and Canadian think tank reports. On all three corpuses, we applied the computational methods for distant reading that include term frequency study, Term Frequency–Inverse Document Frequency (TF-IDF), and term paragraph co-occurrence. The programming language we used for the computational methods is Python.

Research Objective: The objective of the distant reading study is to (1) incorporate grey literatures from industries, think tanks, policy institutes and organizations that are complementary to the academic literature included in the close reading, and in turn, (2) to uncover the patterns behind the corpuses from a quantitative perspective.

Document Collection and Selection: The full list of the selected consulting firms and Canadian think tanks is in Appendix E. We used Google Advanced Search to collect PDF files from the selected firms or think tank websites that contain certain employment-related keywords and are dated from 2015 to 2021. The keywords are "Employment", "Unemployment", "Jobs", "Labour / Labor", "Skills", "Talents", "Works/Workers", "Vacancies", and "Occupations". Finally, to determine which documents to be included in each of the three corpuses, we applied a series of rules that we applied to the systematic literature review (see above). This resulted in 300 reports from consulting firms and 102 reports from Canadian think tanks.

Text Extraction and Text Cleaning: We extracted text data from the collected PDF using the Python library *PyPDF2*[11] . We removed the reference and bibliography section by stopping the extraction process where a page starts with "references" or "bibliography". We then ran a series of steps for text cleaning, including removing non-ASCII characters, removing punctuations, removing stop words, and lowercasing.

Term Frequency Study: In the Term Frequency Study, we counted the occurrences of specific terms in each corpus. The terms are surrounding the subjects of jurisdictions, technologies, and industries.

Jurisdiction Terms: Country names mentioned in each corpus were identified in two steps. First, we used spaCy's *Name Entity Recognition* [16] Python library to identify any possible geographical entity. This will return the exact texts found in the documents, for example, "New York", "USA", or "United States". Next, we ran each extracted geographical entity through *pycountry*[12] Python library; this allowed us to keep only country-level geographical entities and also unify the captured country names.

9. https://clarivate.com/webofsciencegroup/solutions/webofscience-scie/
10. https://clarivate.com/webofsciencegroup/solutions/webofscience-cpci/
11. https://pypi.org/project/PyPDF2/
12. https://pypi.org/project/pycountry/

Industry Terms: The industries were identified with the guideline of *North American Industry Classification System (NAICS) Canada 2017 Version 3.0*[13] . Under the framework of the classification system, the industries are nested within five levels. We used the first-level industries as main segmentation labels, and included terms up to second-level in the search.

We first broke the first-level industry label to individual terms. For example, "Agriculture, fishing, hunting and trapping" is broken down to "Agriculture", "Fishing ", and "Hunting and trapping". We then included the second-level industry terms that are not covered by the first-level labels. For example, the following sub-industries are also counted as "Agriculture, fishing, hunting and trapping"— "Crop production", "Animal production", "Aquaculture", "Forestry", "Logging", "Fishing", "Hunting and trapping", "Agriculture", "Farming", "Groves", "Greenhouse", "Floriculture", "Nursery" and "Timber tract". Finally, we rearranged the grouping to be similar to NAICS 199714 industry grouping to one-digit Standard Industrial Classification (SIC) Codes 1987[15] . The final list of industry terms and their groups is listed in Appendix F.

Technology Terms: We identified a list of technology terms that are AI-related and relevant to our study. The list of technology terms can be found in *Methodology of Systematic Literature Review Data,* Appendix A.5.

Numeric Data Extraction: We used spaCy's *Name Entity Recognition* [16] Python library again to capture numbers used to describe quantities, percentage, and money in order to get a glimpse of the quantitative trends and prediction inside the corpuses. We first captured all entities that are labelled "CARDINAL", "PERCENT", "MONEY", and "QUANTITY". For "CARDINAL" and "QUANTITY" entities, we further filtered the results by including only the entities that contains "thousand", "million", "billion" or "trillion", then combined all the results to "Quantity".

Term Frequency–Inverse Document Frequency (TF-IDF): We used TF-IDF as a statistical measure to evaluate how relevant a word is to a document in the three corpuses. TF-IDF is calculated by multiplying two metrics—how many times a word appears in a document, and how many times the same word appears across the entire collection of documents [29]. A word that occurs frequently in document A would be assumed to be relevant to the particular document. However, if the same word also appears frequently in other documents, it is unlikely to be significant to document A.

We used Scikit-learn Python library [25] to conduct TF-IDF calculation for retrieving a list of keywords that are relevant to each corpus. The library also permits us to calculate TF-IDF scores by bigrams (sequences of two words). TF-IDF was applied to both single words and bigrams in our study.

Term Co-Occurrence: The word distance study is conducted to help us understand the closeness between employment-related terms like "employment", "unemployment", "labo(u)r(s)", "skills", "retraining/reskill(ing)/upskill(ing)", and "prediction/forecast", which we can use to infer the relationship between these terms and, selected industries and technologies. The unit of co-occurrence is document paragraphs. For each paragraph in a document, we sought the occurrence of any employment-related term, and then sought if any industry term or technology term occurs in the same paragraph. In one case, we also looked at altogether the co-occurrence of employment-related terms, industry terms, and technology terms in one paragraph.

13. North American Industry classification System (NAICS), Canada 2017 Version 3.0 Ottawa, Ontario: Statistics Canada, Standards Division; 2017. Available from: https://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVD&TVD=1181553
14. NAICS, North American Industry classification SYSTEM, Canada 1997 Ottawa: Statistics Canada, Standards Division; 1998. Available from: https://www.statcan.gc.ca/eng/subjects/standard/naics/1997/introduction
15. Table: Comparison of All Major Industries Between One-Digit SIC Code and Two-Digit NAICS Code Wyoming Department of Employment, Research & Planning; 1997. Available from: https://doe.state.wy.us/lmi/0497/0497t1a3.htm

3.1 Non-Text Based Data Sources and Methods

Non-text based data sources are listed below. In most cases, we gathered descriptive statistics, graphed and compared data over time, overlayed multi-year projections, and performed cross tabulations. In cases where specific methods beyond descriptive statistics and comparisons over time were used, we detail the methods for each data source below.

- **Government Statistics and Derived Projections:** We accessed data directly from Statistics Canada, US Bureau of Labor Statistics, and US Bureau of Economic Analysis. From these sources, we downloaded, combined, and analysed R&D investment data, labour market data (vacancies and employment data), labour force characteristics, gross domestic product (GDP) by sector, and investment data. The data accessed was from 2010 to present wherever possible. The list of data sources used for these analyses are provided in Appendix H.

- **International Federation of Robotics (IFR) Data:** We downloaded and analysed annual world and Canadian industrial robot installation data from IFR for 2011 to 2019. We also downloaded and compared projection data from IFR for world installations of industrial, professional service, and personal service robots from 2005 to 2023.

- **Compute Canada:** We collected data about the number of hardware requests for Graphics Processing Units (GPU) and Central Processing Units (CPU) from Compute Canada's Annual Resource Allocation Competition between 2012 and 2020. Trends in requests for CPU and GPU resources for research support were identified.

- **NSERC report data:** We used data from annual NSERC reports that provide comparative statistics about the Discovery Grants and Research Tool and Instruments Competitions including number of applications, number of awards, success rates, and average grant amounts broken out by career stage, university, and evaluation group. We gathered statistics for the Computer Science, Math and Statistics, and Electrical and Computer Engineering evaluate groups for each year from the 2014-2015 competition to the 2019-2020 competition, inclusive. Because the 2020-2021 report was not available at the time of our analysis, we used the NSERC Awards Database to calculate the number of awards in each of the three evaluation groups for 2020-2021 (success rate data was not available from the Awards Database).

- **USPTO & CIPO data:** We gathered US patent filing data from the AppFT database, maintained by the United States Patent Trademark Office (USPTO), and Canadian patent data from the Canadian Intellectual Property Office (CIPO) for January 2019 to March 2021. Detailed patent filing data in Canada is only made available after a considerable time lag. For example, the USPTO and the CIPO report that applications generally become public 18 months after filing. Therefore, for the CIPO data, we considered aggregate patent data and total number of filings rather than breaking out detailed information about data science-related patents. For the USPTO data, however, we developed and used a novel method to collect weekly patent application data (between January 2015 and June 2021) in order to conduct a detailed analysis of data-science-related patent filings. Our analysis method takes advantage of the fact that there are regular patterns in the fraction of non-published patents and filing publications lags across time periods. In this way, changes in the number of observed patents filed and published within a timeframe can be used to provide some information about changes in patenting behavior. Details about our method are provided a recent paper which will be made available by request [5].

- **ML Python Package Downloads:** While there are multiple sources where one can download ML-related Python libraries, Anaconda's condastats statistics were gathered. This source was chosen since Anaconda is touted as the world's most popular data science platform with over 25 million users across 235 regions currently reported, and over 2.4 billion package downloads in 2019[16] . We gathered statistics on downloads from condastats of the most popular Python ML packages (tensorflow, pytorch and keras [10, 26, 28] over the period January 2019–December 2021 (data was downloaded on March 9, 2021).

16. https://www.anaconda.com/about-us

4. Results

In this section we return to answering our questions of interest and organize our findings for the first two of our themes outlined in the Objectives section above. Specifically, for the first theme we review the evidence on trends in the adoption and diffusion of AI and data science technologies pre- and post-COVID, while for the second theme we focus on the labour market consequences (skills, employment, unemployment, etc.) of the technological change. The policy implications (our third theme) are discussed in Section 5 below. For the purpose of our exploration, we generally focus on data and publications from 2015 to present whenever possible. This timeframe provides five years of pre-pandemic information that we can use to assess trends prior to COVID-19. Moreover, it is against this backdrop that we can assess the potential impacts that the events of the past year have had on knowledge creation in the fields of AI, data science and robotics.

4.1. Theme 1: The Shifting Landscape: Adoption and Diffusion of AI and Data Science

To understand labour market transitions in an increasingly digital economy, it is important to first explore evidence on the current investment and the path of the development, adoption, and diffusion of innovations in the fields of AI, data science and robotics since these factors are key determinants of productivity growth, and, as a result, the amounts and types of labour required in the economy.

By reviewing recent trends at both the aggregate and sectoral levels, we can gain insights as to sectors that are currently adopting the technologies or plan to adopt them in the near future. This, in turn, will help identify areas where labour and skills sets are being most impacted by the investment in these technologies. As such, we begin by examining a variety of data sources to help determine the speed of innovation and adoption pre-COVID 19, and then seek to uncover if there has been any marked slowdown in the paces following the onset of the pandemic. The path of adoption and diffusion following the onset of the pandemic will depend on the impact of the two related components. The first is the speed of adoption and diffusion of AI, data science and robotic related technologies that had already been commercialized prior to the pandemic (i.e., recent pre-existing innovations that are in the process of diffusing). The second component relates to the impact of the pandemic on the pace of development of new innovative technologies in the area. Changes in the speed of either component will change the predicted path of future technological change, and therefore, the path of labour market changes associated with those changes.

4.1.1. Trends in adoption and diffusion of commercialized technology

We begin by exploring evidence on the pre-pandemic investment and adoption of AI, data-science, and robotic technologies. During our review of available data and literature related to the subject, it became clear that disaggregate data related to the current speed of adoption of the technologies we are investigating are not readily available either for Canada or across countries in general. The most closely related statistics available are for the ICT (Information and Communication Technologies) sectors. The numbers in a recently released report by Innovation, Science and Economic Development Canada (2021) highlights available data and recent trends in the contribution of these sectors to the Canadian Economy.[17]

According to the report, there are over 44 thousand companies in the Canadian ICT sector employing a workforce of over 671 thousand workers in 2020. Over 40,000 of the firms fall in the software and computer services industries with the remaining companies generally falling into the categories of ICT in Wholesaling, Manufacturing and Communication services. Most of the firms in ICT employ less than 10 people with only 119 companies employing of 500 workers. However, as ICT related technologies have been adopted by companies across the economy over time, the ICT sector has been responsible for over 27% of Canadian GDP growth between 2015 and 2020, and, in 2020, it represented 5.1% of Canadian GDP.

17. See https://www.ic.gc.ca/eic/site/ict-tic.nsf/eng/h_it07229.html

Data from the report also highlights that revenue and employment across the ICT related sectors during the pandemic tended to do better than in most sectors of the Canadian Economy, but the pandemic clearly slowed growth with the magnitudes of the effects varying across the ICT sub-sectors. Revenue and employment in the software and computer systems sub-sector increased to $95.741 billion and 463,071 workers, while revenue in ICT manufacturing fell to $7.864 billion and employment declined to 33,883. ICT wholesaling revenue increased to $58.266 billion while maintaining a stable level of employment at 58,505 workers. Revenue in the communications service ICT sub-sector remained constant, but employment fell by 115,650.

The report also highlights that significant decline in sales for the ICT sector is still expected to materialize causing a challenge for many of the firms in the near future. The longer-term impacts of the pandemic are yet to be determined with the firms in the sector facing significant headwinds from a global semiconductor shortage, potential higher competition for talent given the increased viability of remote work, and the implementation of "buy local" policies in major export markets such as the US and France.

4.1.1.1. Canadian Business Investment in software and equipment

Much of the adoption of ICT and robotic technologies occurs through the purchase of software, equipment, and machinery. The available data from Statistics Canada show that while Canadian firms have been investing in equipment and machinery, the levels of investment per worker have not kept up with other major industrial economies, such as the United States. Should this trend continue, it is evident that Canadian firms may fall behind their American counterparts on key dimensions that will impact their levels of productivity and competitiveness. Since disaggregate numbers on the type of software and equipment purchased by industry over time are hard to come by, we have attempted to compile data from a variety of sources to gain some insights on patterns of adoption pre- and post- pandemic.

4.1.1.2. Investment Trends in Robotic Installations

Our first source of statistics was collected from a review of reports from the International Federation of Robotics (IFR). The data from the most recently available publications show the robust installation of service and industrial robots both globally and domestically. Although, the data does suggest a flattening of Canadian firms' new industrial robot installations starting in 2018, and a slight slowdown in world-wide installations in 2019, this would suggest that, even prior to the pandemic, the rate at which robotic technologies was replacing labour through the implementation of industrial robot technology may have slowed somewhat.

To shed further light on what the short-term forecasts for adoption in this area are, and how they may have been impacted by the pandemic, we reviewed the forecasts provided by the International Federation of Robotics from 2011-2019[18] . Since the forecasts are not consistently produced for each country, we examine the projections for world-wide installations over time. From these numbers, five takeaways are apparent. First, the IFR expects that the 2020 levels of industrial robotic installations will be 50-60% less than the 2019 levels. Second, the forecasted levels of industrial installations post-pandemic over the next few years are strongly dependent on the speed of economic recovery. Third, regardless of which of the reopening scenarios is utilized, all forecasts suggest that the next few years will see the number of installations below the 2019 levels. Fourth, new adoption of professional service robots continues to expand as does installations of personal service robots. Fifth, the expected rate of adoption of both professional service and personal service robots is forecasted to be slower over the next few years relative to the levels forecasted prior to the pandemic. Overall, the evidence would suggest that there is expected to be continued demand for workers involved in the creation and manufacturing of robotic technologies over the short run – albeit at a slower pace than was forecasted pre-pandemic – and the rate at which robots replace humans in the manufacturing sector is likely to be slower in the short-run given the severe economic downturn caused by the pandemic.

18. Graphs and charts for this data are available in our Mini Report provided in Appendix J.

4.1.1.3. Interest in AI–related Software

Given that the type of official disaggregated timeseries data at a monthly or quarterly level we would optimally like to examine to track firms' adoption of AI is unavailable, we collected a series of alternative statistics to fill the data gap (See [4]). Specifically, data on the volume of Google and Bing searches for Machine Learning (ML) Python package names and download rates of ML Python packages are collected over time. This search behaviour is used as a proxy for diffusion since it reflects individuals' desires to learn about specific ML Python packages over time and where to obtain them which should be directly related to development, training and implementation of these tools and their related methods. Figure 2 shows the volume of searches for ML Python packages in Canada from January 2010 to December 2019 (pre-pandemic) and we can see growth in interest in these packages starting in 2016.

If we zoom in to look at the data pre- and post-pandemic search data (see Figure 3 from [4]), we see signs of a potential disruption in AI related activities due to the pandemic. In particular, the volume of Google and Bing searches for ML Python package names decreased during the months of the pandemic with the decreases being more noticeable during the period where lockdowns and business closures became common. For both the Global and Canadian series, we see a slight increase in search volume after the annual seasonal drop in December 2020, but overall searches still remain below the pre-pandemic download volume. Given that search behaviour changes across dates is expected to be correlated with changes in interest in the use of these data science related packages, it would appear that these numbers signal some disruption and delay in the adoption and diffusion of data science innovations. This disruption will likely worsen should there be a significant resurgence of COVID-19 cases related to the Delta variant requiring further lockdown of businesses in Canada and globally.

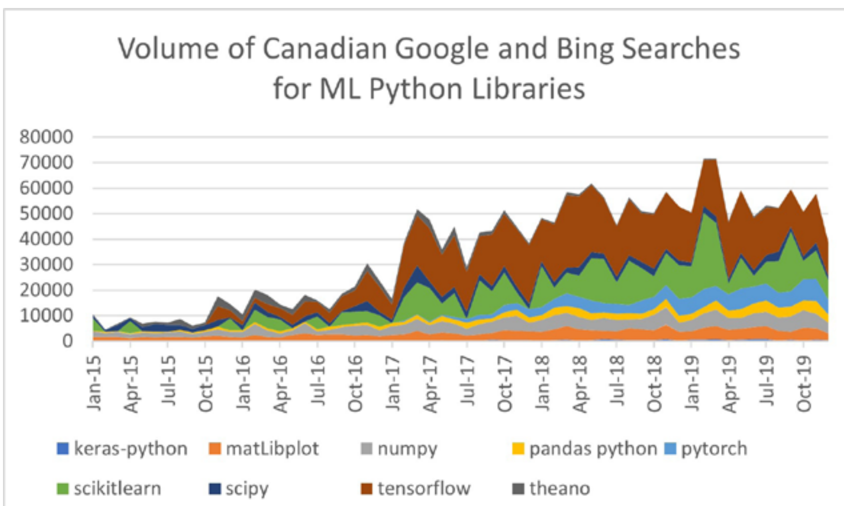


Figure 2: Volume of Canadian searches for selected ML Python libraries.

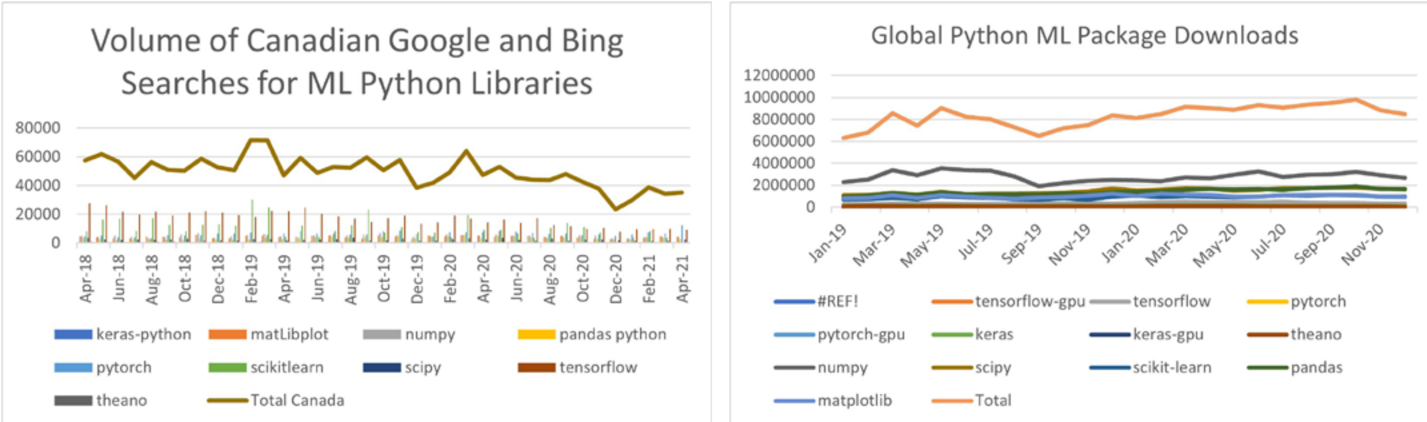


Figure 3: Searches for ML Python libraries pre- and post-pandemic, globally (a) and for Canada (b).

To further confirm the patterns seen in the search volumes, we also explored data about the number of package downloads from Condastats for the tensorflow, pytorch and keras packages over the period Jan 2019- December 2021 (see Figure 4). Consistent with our contention that the decline in search behaviour is correlated with downloads and installations of packages, we see the Condastats' data appears to follow the same downward trend following the COVID-19 surge in cases in early 2020.

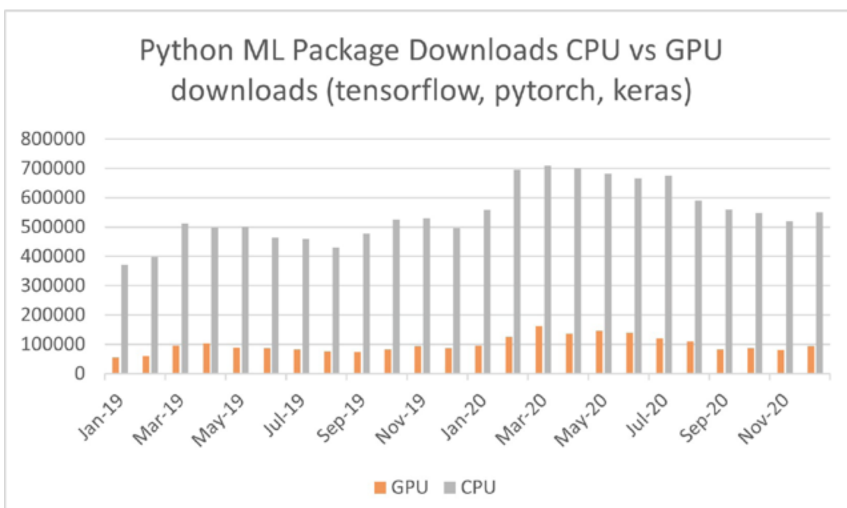


Figure 4: Downloads of ML Python package downloads.

4.1.1.4. Trends in Reporting on AI in the Media

While trends in journal articles and conference publications have been used in the past to track innovation and output of R&D activities (see [3] and [4]), examining counts in newspaper articles tied to AI and data science can be useful in discerning implementation of these tools and techniques in industries and businesses. The rationale behind newspaper article-based metrics is similar to that of other bibliometric measures. Newspapers seek to cover events of interest to their current (and potential) since newspapers make money by selling copies and access to articles and/or generating funds through selling advertisements. Therefore, given that implementation of data science and AI related innovations have important implications for employment opportunities, job loss, training required for future jobs, as well as firm profitability, international competitiveness and Government policies, articles will appear as more firms are adopting these innovations over time and advances in these areas are unveiled.

As such, we present coverage of AI and data science related topics in English language newspapers in Factiva's[19] database , in Figure 5 and also present some statistics confirming the same trends exist when we consider only US and Canadian newspapers. The resulting data shows that, independent of whether articles are restricted to be both on the topic of AI / data science AND tagged to be related to the region the newspaper is published in, or whether they are limited to just focus on articles referencing AI / data science related terms, coverage grew rapidly until 2018, slowed during 2019 and then fell further during the pandemic. This decline in the number of newspaper articles that discuss data science related terms again suggests that the pandemic likely slowed the pace of commercialization and adoption of these technologies. Although, there more recent rebound seen in Figure 6 suggests that as the economy has reopened, there is evidence in a resurgence.

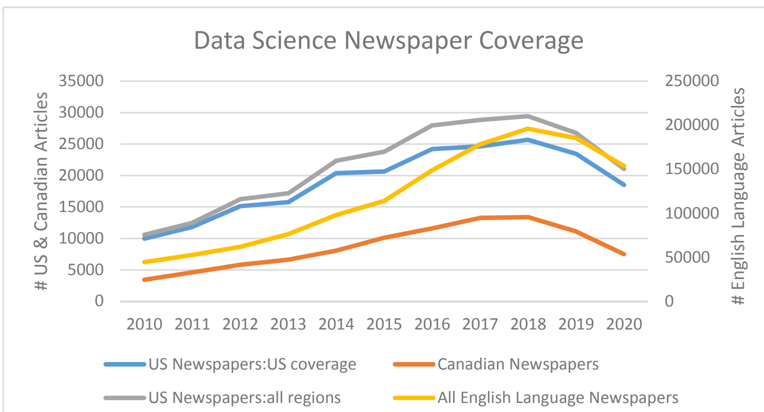


Figure 5: Coverage of data science topics in newspapers.

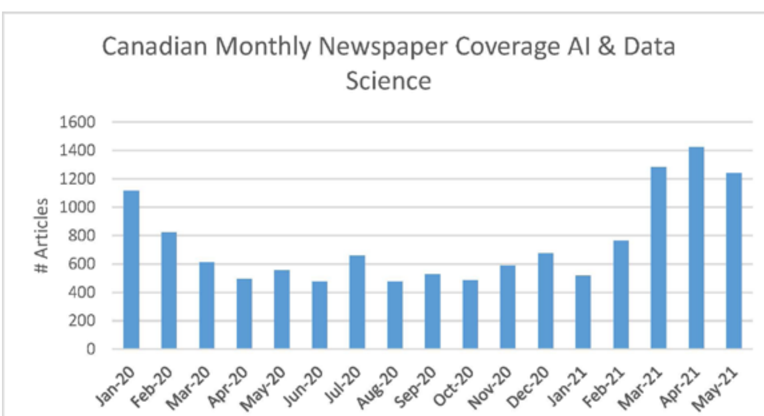


Figure 6: Coverage of data science topics in Canadian newspapers from Jan. 2020 to May 2021.

19. https://professional.dowjones.com/factiva/

Next, we examined patterns of which industries were most frequently mentioned in the newspaper data. For this exercise, we utilize the industry tags Factiva assigns to its articles. The observed patterns should provide some additional insights into areas where implementation is taking place or is likely to take place in the near future. The findings reveal that the sector discussed most often is the technology industry itself. This is not surprising since it is critically linked to the development and commercialization of new technologies in the area, and its own demand for labour and changing skill sets will feature prominently in the discussion of the path of technical change. The next most frequently mentioned sectors are the financial services industry, business and consumer services, retail and wholesale trade, media/entertainment, the automotive sector and the industrial goods sectors. The patterns of mentions are also not uniform across the sectors. For example, during the pandemic when the overall number of articles related to AI, data science and robotic technologies fell, articles related to these technologies and health care rose as the innovations in the area were utilized to help track the pandemic and aid in the search for treatments and diagnostic tests. Moreover, as the economy is reopening, it is clear that the discussion on the innovations in relation to other sectors are again front and center. By June 2021, the number of articles related to the technical change in the retail and wholesale trade, agricultural and industrial goods sectors have surpassed the totals seen in 2020. Moreover, should the current trends in the average rates of publication by industry continue for the remainder of the year, the only sectors that would not have the number of articles surpass their 2020 totals are the leisure and hospitality, real estate and construction, and transportation related industries, although the totals for industrial goods, retail and wholesale trade, health care/life sciences, business and consumer services, agriculture, utilities and the technology sectors itself would surpass their 2019 pre-pandemic levels. Currently, this wide-spread rebound would suggest adoption of commercialized technologies are returning towards more normal levels.

4.1.1.5. Other Evidence on Future Adoption of AI, Data Science and Robotic Technology

The evidence presented above, regarding the downward pressures on investment from COVID and the related economic recession, as well as the more recent signals that the economy is beginning to return to more normal levels of investment are also in line with International Data Corporation (IDC)'s estimates for Canadian spending on digital transformation and recent evidence from the Bank of Canada's Business Outlook survey. Specifical IDC reported in June 2020 that they forecasted Canadian spending on digital transformation to reach $28 billion in 2020 with a growth rate of 7% in spite of the challenges presented by COVID-19. They noted that the growth was notably slower than 2019 due to the effects of the pandemic, but stressed that the spending was expected to recover quickly in the following years (2021-2023) with a five-year CAGR of 13%[20]. In addition, their estimated pre- and post-COVID growth rates by sector indicated a 13% decline for distributions and services, a 6% decline in digital transformation spending in the financial and infrastructure related sectors, and a 7% decline in the public sector. Manufacturing and resources sectors were forecast to have the largest decline in the growth for digital transformation spending falling from 18% to 3%. IDC's prediction that the spending would quickly recover post pandemic is consistent with the Bank of Canada's Summer 2021 Business Outlook survey findings that firms are planning increased investment in machinery and equipment over the next 12 months[21] , and the Bank's current view that that the future growth rate in potential GDP will rise due to the increases in current and planned investment in digitisation and the increased transformation signalled by Canadian Firms' demand for digital skills is growing rapidly[22].

4.1.2 Trends in related innovation

In additional to impacts on the adoption of commercialized technologies available prior to COVID-19, there may be longer lasting impacts of the pandemic if evidence suggests that it also had a negative impact on the overall creation and development of new AI, data science and robotic technologies. To explore the pre- and post-pandemic trends in innovation, we review data on R&D expenditures, grants to researchers, patents and journal publications over time. These statistics are chosen since R&D is vital input into the creation of new innovations, and the output of these endeavors can be seen in patents and journal publications. These metrics are examined since they are frequently used in the field of economics to determine the rate of technical change and knowledge advancement (see [2] and [14]).

20. See https://www.idc.com/getdoc.jsp?containerId=prCA46542820 for their summary of findings.
21. See the survey data presented at https://www.bankofcanada.ca/publications/bos/business-outlook-survey-data/
22. See the Bank of Canada's April and July Monetary Policy Reports available at: https://www.bankofcanada.ca/publications/mpr/

4.1.2.1. Research and Development Trends

To examine the trends related to the inputs into knowledge creation in the area, we examine two sources of statistics. The first is the reported levels of R&D in the Canadian economy, and the other related to grants to researchers in the higher education sector. The data and figures below are reproduced from our recent paper [4].

Statistics Canada Research and Development statistics: Each year Statistics Canada conducts surveys to determine the levels of Canadian R&D. These data are broken down by type of funder of the R&D activities as well as by performing sector. While this official data does not provide details that would allow us to uniquely identify R&D committed to AI, data science and robotic related projects, it provides some insights into pre-pandemic trends in support for natural science related R&D as well as revealing what the funding intentions were before the pandemic occurred for 2020[23].

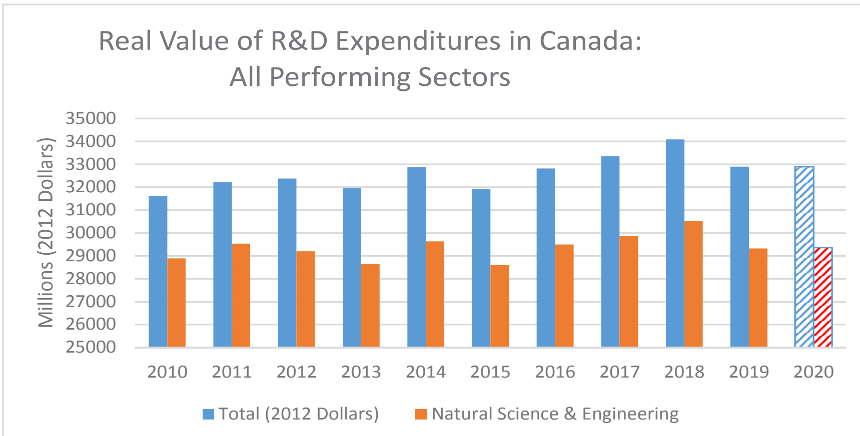
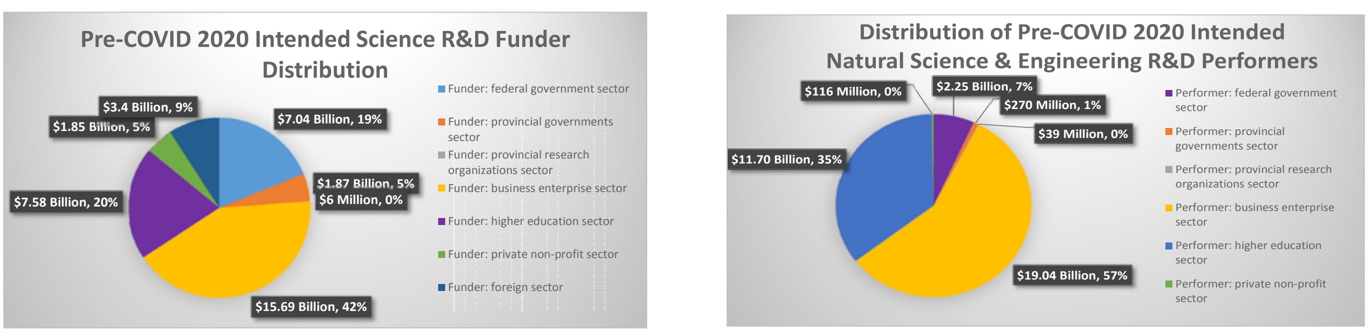


Figure 7: Total and natural science and engineering R&D expenditures in Canada from 2010 to 2020 (reported).

As Figure 7 highlights, growth in inflation adjusted R&D expenditures in Canada have been trending upwards over the 2010-2018 period, and while 2019 saw a decline in expenditures, the reported planned spending for 2020 (in nominal dollars) would have seen inflation adjusted values slightly increase over the 2019 levels. The major anticipated sources of funding and expected performers of R&D activities for 2020 indicated by the data collected prior to the pandemic are displayed in Figure 8 (a) and (b)[24] .



(a) *(b)*

Figure 8: Anticipated sources of R&D funding (a) and expected performers of R&D (b).

23. Spending intentions for 2020 were collected before the onset of COVID-19
24. The distribution across groups is consistent with the previous year's patterns.

Two things are evident from the statistics in these figures. The largest funder and performer of natural science and engineering R&D activities in Canada is the business enterprise sector, with the second largest performer being the higher education sector. While these statistics do not allow a breakdown to the level of AI, data science and robotic related R&D, alternate statistics, displayed in Figure 9, shows that the level of R&D expenditures related to information and communication technology (ICT) and computer and electronic manufacturing in business enterprise in-house R&D, has been growing over time as the economy has increasingly transitioned to a more digital economy[25] and together these two sectors now account for about 46% of total business enterprise in-house R&D[26] . Similar to the data at the more aggregated level, 2020 spending intentions for businesses in these sectors overall were also expected to increase over the 2019 levels.

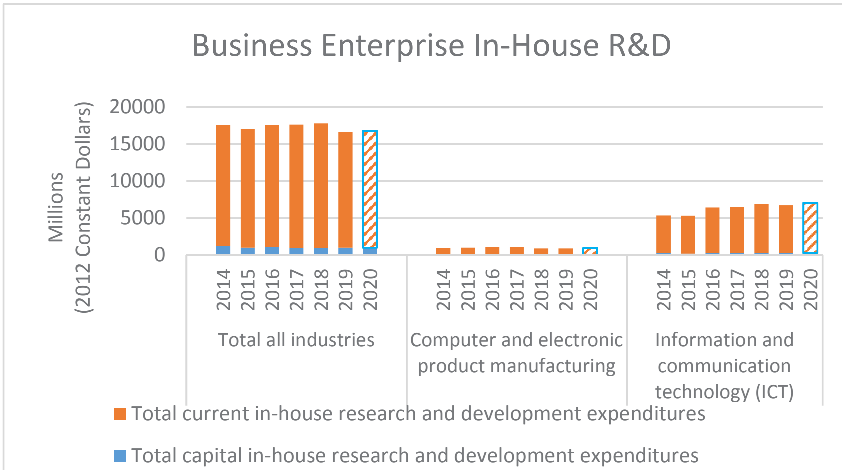


Figure 9: In-house R&D for all industries, computer and electronic product manufacturing, and ICT.

Unfortunately, the pandemic would have likely altered their plans due to the large impact on economic activity, industry profits, and changing revenue streams. For example, prior to the pandemic, the average annual growth rates in real gross domestic product in the computer and electronic product manufacturing and the ICT sectors over the 2015-2019 period were approximately 3.2% and 4.64% respectively. In contrast, their annual growth rates during 2020 were -11.7% for the computer and electronic product manufacturing sector and only 2.8% for the ICT sector [33]. Therefore, given that R&D represents an investment by firms, and organizations would have likely forecast higher growth rates for their sectors than what was realized at the time that intended expenditures were collected by Statistics Canada, the realized reduction in profits and revenues that was experienced by most firms will have likely impacted realized investment levels, including R&D expenditures, negatively.

Given that the next largest funder of Canadian R&D is the Federal Government and higher education sectors (see Figure 7), we also report the actual (2010 - 2019) and intended 2020 spending for the Federal Government's support for the higher education sector's R&D in Figure 10. These data, in combination with the Federal Government's announced funding increase for science and technology and R&D expenditures during the pandemic, suggest that research funding available for this sector was less affected than that for the business enterprise one[27]. However, as we see from other metrics related to research support from Canadian granting agencies presented below, it would appear that the pandemic still likely disrupted the researchers' planned and future projects in data science and AI related areas.

25. In-house RD spending normally represents about two thirds of overall business sector R& D funding. See e.g., https://www150.statcan.gc.ca/n1/daily-quotidien/201209/dq201209b-eng.htm
26. Source: Statistics Canada. Table 27-10-0333-01 Business enterprise in-house research and development expenditures, by industry group based on the North American Industry Classification System (NAICS), country of control and expenditure types (x 1,000,000) https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2710033301
27. See https://www150.statcan.gc.ca/n1/daily-quotidien/210610/cg-e001-eng.htm for a recent discussion on overall Federal Government spending on science and technology during the 2020/21 fiscal year and Statistics Canada Table 27-10-0026-01 Federal expenditures on science and technology, by major departments and agencies - Intentions (https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2710002601) for evidence that the Natural Sciences and Engineering Research Council of Canada's 2020/2021 budget increased by $10 million dollars during the 2021/2021 fiscal year.

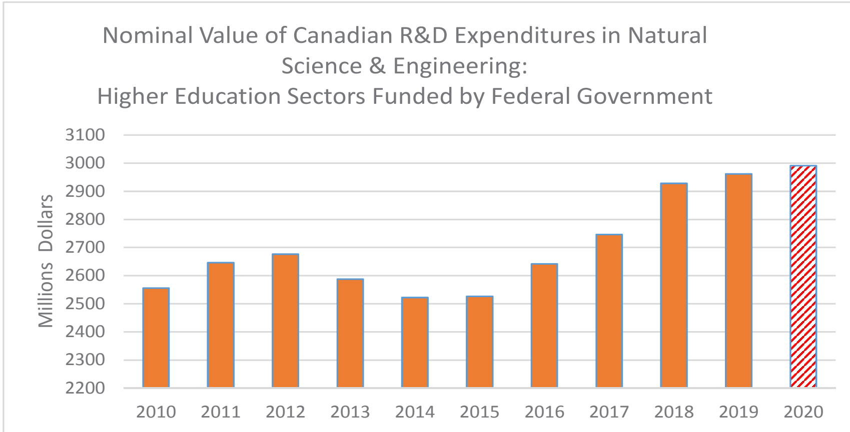


Figure 10: Actual and intended R&D spending in the natural sciences and engineering by federal government.

Compute Canada Infrastructure Support Requests: Many of the new advances in AI and ML require substantial hardware support. Therefore, given the lack of direct measures of disruption for research in the area, and its recognized importance for the future of the Canadian economy, we complement the official R&D data with information on the amount of infrastructure support requests by application year made through Compute Canada's annual resource allocation competition from 2012 to 2020. Overall, the data in Figure 11 shows large increases in the number of computer hardware requests for CPU and GPU resources to support research in the pre-pandemic granting cycles. However, it also suggests a potential disruption occurred in academic research related to AI and data science after the onset of the pandemic. This is inferred by the significant decrease in GPU allocation requests and a slowdown in the asks for CPU support in the 2020 application year, which took place in the Fall of 2020. As such, it would seem that there was a lower level of planned R&D activity in the grant period (i.e., from April 2021 through March 2022) which would further dampen the pace of Canadian R&D production at least in the short run.

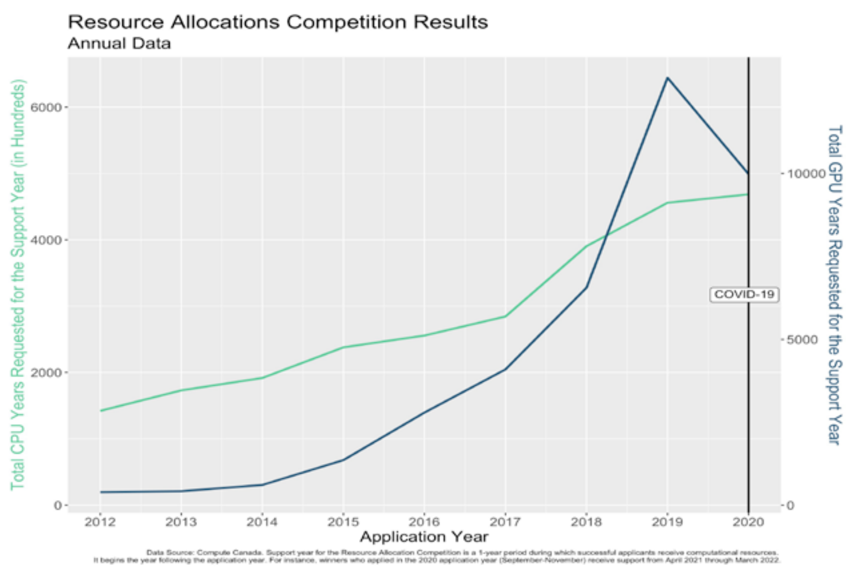
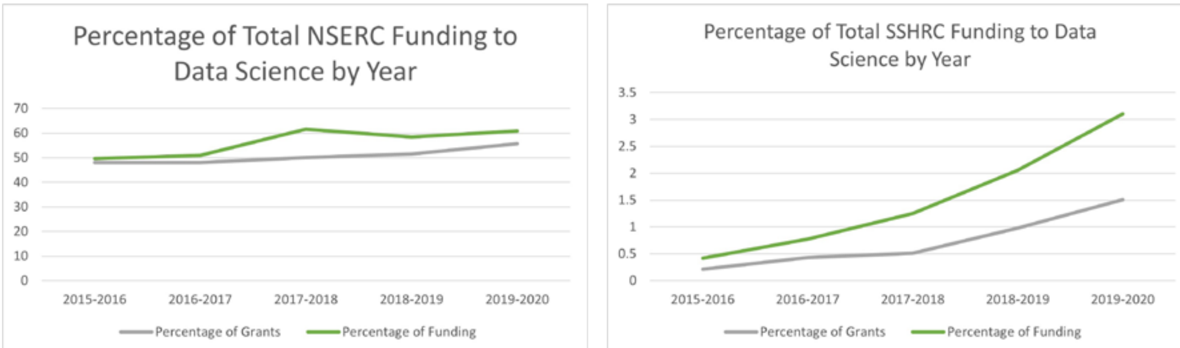


Figure 11: GPU and CPU requests to Compute Canada's Resource Allocations Competition (2012 to 2020).

NSERC/SSHRC funding to AI and data science related research: Based on the data were we able to compile from the Social Science and Humanities Research Council of Canada (SSHRC) and Natural Sciences and Engineering Research Council of Canada (NSERC), the absolute number of grants and the amount of funding for both NSERC and SSHRC in the area of data science has increased from 2015/2016 to 2019/2020. However, if we look at the percentage of all NSERC funding, the data science project allotment has remained relatively static between 48% and 56% of the total number of grants funded and 50% to 62% of the total funding amount (see Figure 12 (a)). The average funding per NSERC grant in data science areas ranges between 81-97% of the average overall funding amount per grant. The situation for SSHRC funding and grants is quite different (see Figure 12 (b)). The percentage of total grants and funding that go to data science related projects in SSHRC is much lower than that for NSERC (<=3.1%); however, the percentage has grown considerably between 2015 and 2020. Furthermore, the average funding provided to data-science related SSHRC projects is between 1.8 and 2.4 times the average for all SSHRC projects compared to NSERC projects (where the average funding for data science projects is less than that of non-data-science projects). The growth in SSHRC funded projects related to data science is, at least partly, attributed to the growing interest and government priorities in social issues related to the effects of AI and data science adoption on new tools available for research as well as the effect on privacy, intellectual property rights, competitiveness, industrial structure, labour markets, income inequality, and the need for policies and regulations to adapt to the changing landscape.



(a) *(b)*

Figure 12: Percentage of funding to data science topics for NSERC (a) and SSHRC (b) by year.

Since the goal here is to understand trends in the development of new tools and methods, and hence the path of future innovation in this area, we also looked at data from the NSERC Discovery Grants over time. Most Canadian Researchers working in the natural sciences and engineering maintain support for their ongoing research through an NSERC Discovery Grant (DG), and, in some cases, DGs are used as eligibility requirements for other funding opportunities such as Research Tools and Instruments grants. This makes DGs related to the Computer Science, Mathematics and Statistics, and Electrical and Computer Engineering DG Committee areas a good proxy for the quantity of academic activity in these areas. A summary of the data related to the number of grants awarded, success rates and values of awards are found in Table 1. There are a few notable observations from these statistics. First, it is clear that there has been a large drop in awarded grants in the 2020-2021 period. Electrical and Computer Engineering appeared to have experienced the largest decline, but even the least impacted of the three groups (Computer Science) had a drop of approximately 41%. Second, the success rates by committee have typically fluctuated from around 60%-87% for the 4 years prior to the pandemic. Even though the success rate statistics by committee for the 2020-2021 competition are not yet available (indicated by n/a in Table 1), if the success rates are similar to those in the recent past, the fall in awards again points to a large decrease in applications to support new projects. The magnitude of the drop is at least partly explained by the fact that, in recognition of the extraordinary impact of the pandemic and lockdowns on the ability to work on Campus in offices or in labs, NSERC announced in April 8, 2020 that, “To lessen the impact due to COVID-19 and to support all of our researchers and highly qualified personnel, all active Discovery Grants can elect to receive a one-year extension with funds at their current funding level ... Grantees due to apply in competition 2021 can elect not to apply for funding this summer/fall during these tumultuous times.” . However, it is important to recognize that this additional funding and extension of existing awards was a response to the unprecedented negative impact of the pandemic on research in the higher education sector, and, while the situation in Canada improved somewhat in the first few months following the NSERC decision, the second wave of the pandemic that forced the higher education sector online again in the fall was worse. Overall, the evidence available would point to a substantial disruption to Canadian early-stage R&D in the area.

28. See https://www.nserc-crsng.gc.ca/Media-Media/NewsDetail-DetailNouvelles_eng.asp?ID=1144 and https://www.nserc-crsng.gc.ca/Professors-Professeurs/FAQ-FAQ/DG-SD_eng.asp#1

Table 1: NSERC Discovery Grant statistics from 2016-2021.

	Grants Awarded			Success Rate		
Competition Year	Computer Science	Math and Statistics	Electrical & Computer Engineering	Computer Science	Math and Statistics	Electrical & Computer Engineering
2016-2017	206	185	182	62.4	87.0	63.9
2017-2018	231	193	149	67.2	86.5	64.7
2018-2019	222	204	147	67.0	79.4	63.1
2019-2020	245	175	173	66.7	72.8	60.5
2020-2021	144	89	80	n/a	n/a	n/a

4.1.2.2 Trends in Patenting

Patent applications is the next set of data we examined in our goal to provide information on the potential path of future innovations coming to market. The figures presented below are reproduced from the analysis described in [4] and [5] and highlight the trends in the data available from the United States Patent and Trademark Office (USPTO), and the Canadian Intellectual Property Office (CIPO). Aggregate level data from these offices does indicate that there has been a decrease in the overall number of patents filed during the 2020 year. Figure 13 displays the CIPO's patent filings as reported by their monthly production statistics and clearly highlights the fact that that surges in the number of Canadian COVID-19 cases were related to decreased application filings with the patent filings dropping from 38,825 in 2019 to 36,173 in 2020 (a 6.8% decrease). The USPTO saw a slightly smaller decline (perhaps due to the differential lockdowns and restrictions across the jurisdictions) with a drop off in applications of 24,278 filings from the prior year (i.e., a decline of approximately 3.9%)[29].

The aggregate patent statistics give some support to the hypothesis that COVID had a negative effect on R&D across the board, however, given that patent applications from the USPTO and CIPO are not publicly searchable until months after their filing dates, we needed to rely on our work and method reported in [5] to comment more directly on the pandemic's likely effects on innovation on AI-related patents more precisely. The paper focuses on the US patenting behaviour and utilizes regularities in the pattern of publishing lags for patent applications, and comparisons across months of publication application data accounting for the fact the publicly available data is truncated to produce estimates of the COVID impact on AI related innovations. Specifically, the estimates suggested growth rates for the periods 2017-2018, and 2018-2019 pre-COVID are estimated to be approximately 35%, with the growth rate for 2019-2020 falling to approximately 13.5%-16.2%, with the month over month comparisons also highlighting significant declines in AI-related applications occurring after the onset of the pandemic. Although the error associated with estimates for the most recent months are largest, they do provide some indication that the number of applications in the area are rebounding. Overall, given that many Canadian firms often file patents in the US, and a significant portion of innovations historically implemented by Canadian firms are developed and patented in the US, the trends seen would again indicate that COVID has had a negative impact on the future path of commercializable innovations.

29. https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm

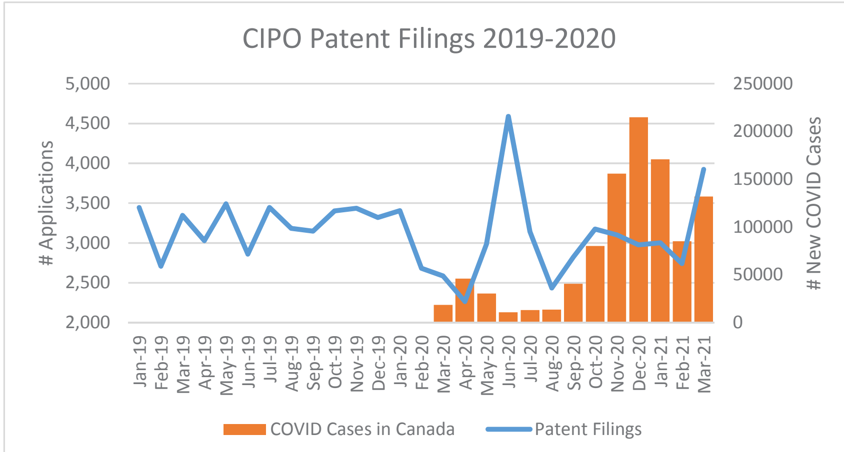
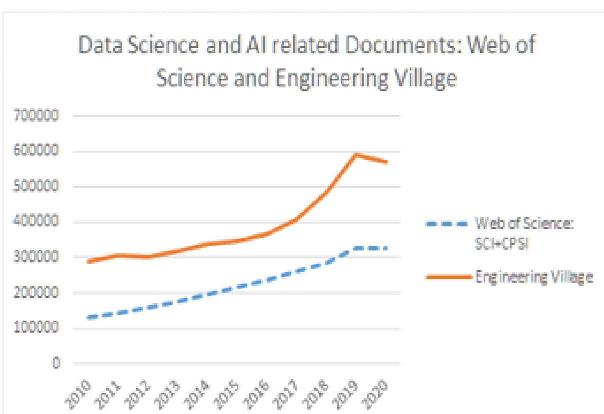


Figure 13: Patent filings in Canada from Jan. 2019 to March 2021 and number of new COVID cases.

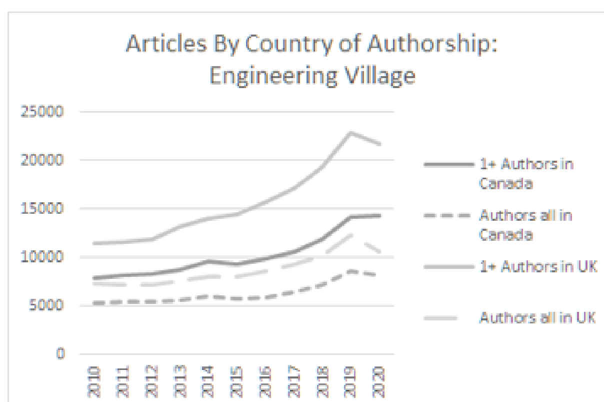
4.1.2.3 Trends in Academic Publishing

It is well known that not all innovation is captured by patent statistics. To account for this fact, we also discuss here the trends in journal and conference publications related to AI and data science indexed in Engineering Village and the Web of Science's Science Citation Index Expanded and Conference Proceedings Citation Index databases and presented in [4]. These data, displayed in Figure 14 (a), depict the tremendous upwards growth of publications over the time period 2010-2019. However, there is a clear break in this trend dated from the onset of the pandemic where the annual growth rate went from 22.1% in 2019, to -3.7% in 2020. Figure 14 (b) shows evidence of a disruption for papers where at least one of the authors of the paper is associated with a Canadian institution, and a larger impact occurring when all authors on the paper had Canadian affiliations.

While the data available to predict the future path of diffusion of both commercialized, and future commercializable innovations, suffers from shortcomings, the preponderance of the available evidence suggests that the pandemic has likely slowed both the adoption of currently available technologies and pace of innovation in key areas associated with AI, data science and robotics. As a result, it is likely that the timing of labour market disruptions and the possible emergence of skill gaps related to the adoption of the associated technologies that were predicted prior to the pandemic will occur at least a few years later than originally forecast.



(a)



(b)

Figure 14: Total number of data science related documents over time (a) and broken out by author country (b).

4.2 Theme 2: Labour Market Consequences of the Technological Change

We now turn our attention to the evidence on the labour market impacts of the technical change discussed above. To present as complete a picture as possible, we reviewed several data sources and examined textual material using the distant read methods and a systematic literature review outlined in Section 3. The summary of our findings are discussed below. It is important to recognize from the onset, however, that the majority of predictions on the labour market impacts, and the research related to the changes in necessary skills, pre-date the onset of the pandemic. Moreover, much of the work that has been undertaken to date has not specifically focused on the Canadian economy. As such, when using the findings to inform future policy, it is important to recognize two elements. First, that COVID appears to have impacted the diffusion rates of current and future developments in AI, data science and robotic related technologies – at least in the short run – and the magnitudes of the impacts is still in question and may well change if there is a significant resurgence of COVID cases that necessitates further extended lockdowns and restrictions. Second, policy makers will often need to infer likely impacts on Canadian firms, industries, and workers using estimates derived by economies with similar industrial structures, such as the US and UK.

The data and research reviewed below highlights five key takeaways. First, as with other technical change, there will be volatility in the job market as the new technologies are adopted by firms. Some new types of jobs will emerge related to future technologies not yet developed, some occupations will expand job opportunities, while employment in other occupations will shrink or disappear altogether. Second, there is significant differences in the magnitudes estimated pre-pandemic, and disagreement on the speed at which the disruption will occur. Third, the amount of disruption and labour displacement that will happen within an economy will depend on the industrial structure of the economy. For example, economies with larger fractions of workers employed in manufacturing jobs that can be automated with robotic technology, will have more workers displaced, all else held equal, than economies with smaller fractions of these types of jobs. Fourth, the amount of support necessary to retraining workers displaced by the adoption of new technologies to obtain employment in new sectors and occupations will depend on factors such as the level of education of displaced workers, the difference between the skill set of the displaced workers and the required skills in the jobs they will transition to. Fifth, the level of intervention required to aid in transition will depend on the speed of the adoption of new technologies and the age distribution of workers. For example, if the pace of the technical change occurs at normal levels, some workers employed in shrinking sectors and occupations will simply retire as opposed to opt for retraining, and new jobs created by the technological change will be able to be filled by younger workers with skill acquired through education, or workers in areas with transferable skills. Unemployment, in this case, remains close to historical averages. If, however, the pace of change is rapid, and the skill requirements of new jobs are sufficiently different from the skill set of the existing pool of labour pool, unemployment rates can soar, and vacancies posted for newly created jobs may go unfilled due to skill gaps and skill shortages.

4.2.1 Trends observed in available data

In this subsection we present some available data from Government sources and derived projections, as well as data from secondary sources, to uncover recent labour market trends pre- and post-pandemic.

4.2.1.1 Current Employment Trends from Statistics Canada

To best understand the potential impacts on Canadian labour markets, it is necessary to first review some general data on current trends in employment overall, and by sector. According to Statistics Canada (Statistics Canada), in 2019, Canadian total industrial aggregate employment was 16,976,382, with this number dropping to 15,572,434 in 2020. Approximately 18% of employment is found in goods producing industries (i.e., forestry, mining & quarrying, utilities, construction and manufacturing), with manufacturing employment making up about half (9.3%) of this, and construction employment being just over 6%. Employment in the service industries is about 80% of employment with the largest components being employed in Wholesale and retail trade (~17%), Health care and social assistance (~12%), Educational services (~8%), Accommodation and Food Services (~8%), Public Administration (~7%) Professional, Scientific and technical services (~6%), and Financial and insurance (~4.5%).

The pandemic, and the related lockdowns, have hit employment across sectors disproportionately[30]. Many employees moved to a remote work environment in sectors/job where that was possible (e.g., Banking, and Education) and E-commerce activities hit record highs as consumers were forced to change their shopping behaviour in response to the evolving health crisis and lockdown measures. The economy has finally started to reopen, and, as the current vacancy and job posting data highlights, workers are being rehired. The future of jobs and employment, however, will still depend critically on the which sectors will adopt the latest technologies, which will help produce, distribute and sell them, and whether the potential labour-savings associated with the technologies will be offset by the creation of new jobs created by their adoption[31]. The speed of transformation will also depend crucially on the availability of workers who process the skills necessary to perform the available jobs. When there is a shortage of labour with the appropriate skills, the related vacancies will go unfilled for longer periods of time even if there are workers who are being displaced from jobs in other industries or sectors due to skill gaps, and costs associated with retraining/relocating labour.

4.2.1.2 Pre-COVID 10-year Projections for Employment Trends

Every two years, the Economic Policy Directorate (EPD) of Employment and Social Development Canada (ESDC) develops long-term projections for 293 occupations at the national level using the models of the Canadian Occupational Projection System (COPS), the 2016 version of the National Occupational Classification (NOC) and data from Statistics Canada. The main objective of this endeavour is to identify occupations where the current and projected states of supply and demand in the markets suggest that imbalances could develop and/or persist over time in the Canadian economy. We review here their most recent projections that were produced and released prior to the onset of the pandemic and cover the period 2019-2028.

A review of the projections shows that 235 of the 293 occupations were deemed to have "balanced" future labour market projections (i.e., the supply and demand for the occupation appears roughly equally). Of the remainder of the occupations, 22 were labelled as being in a future surplus position (i.e., a case where supply exceeds demand), and 36 were assessed as likely to have future shortages (i.e., where demand exceeds supply). In the "shortage" category, 11 of the occupations are related to engineering (including computer, software and mechanical engineering), computer programing, database management and graphical interfaces and design, and 17 are related to the provision of health care. For the shortage group, three are related to engineering (specifically, chemical, civil and mining/geological/petroleum engineering), with the vast majority of other groups being related to data entry, manual labour, and couriers/door-to-door delivery.
The current views expressed by ESDC is that their long-term predicted trends are not expected to be affected markedly by the COVID-19 outbreak since its impacts on the labour force and the economy are generally foreseen to be temporary[32]. However, as we highlighted in Section 4.1 any projections at this point should carefully assess the impact that COVID has had on the path of innovation, since, if the negative impacts are large enough, they will translate into a slowdown in adoption, productivity gains, and labour market transitions. In any case though, a cursory examination of the occupations labelled as being in the shortage and surplus categories would suggest that the pace of adoption of robotic technologies in the mining and manufacturing industries will play a key role in the amount of surplus (and related unemployment) in the manual labour occupations listed, and the levels of shortages faced by the 11 occupations related to computer science and computer, software and mechanical engineering will depend on the diffusion of the AI, data science and robotic related technologies. As we will see below, however, there may be cases, such as occupations in the health care field, where AI and computerization is not expected to significantly displace labour, but where advances in these technologies may result in productivity gains that could decrease the overall costs to society of dealing with shortages in these areas.

30. It increased employment in the company management sector, and decreased employment in all other sectors with the largest declines occurring in the Accommodation and Food Services sector and the Arts and Entertainment Sectors (~ 30% decrease).
31. See e.g., [1] and the references within it for a discussion of the overall employment effects of product vs process.
32. For more information on the projections see their website at http://occupations.esdc.gc.ca/sppc-cops/w.2lc.4m.2@-eng.jsp

4.2.1.3 Recent trends in AI and Data Science related Vacancies and Job Postings in Canada

Even if the effects of the pandemic have a negligible impact on the ESDC's 10 year forecasts, the future short-run path of employment opportunities have been altered. To provide some sense of the current state of employment opportunities, we briefly review some of the current statistics related to vacancies and job market postings. Data on the former is obtained from Statistics Canada while data from the later comes from the Labour Market Information Council (LMIC) who works with partners, including ESDC and Statistics Canada, to enhance the collective knowledge of the skill requirements of jobs in Canada.

The latest release of job vacancies shows that the number of job vacancies across industries increased by approximately 7.9% from the first quarter of 2020 to the first quarter of 2021. This, in large part reflects firms desire to hire labour lost during the pandemic as business reopen. While employment in the professiaonal, scientific and technical services sector is relatively small, it employs many of the computer and information systems professionals in the economy. Growth in the vacancies in this sector appear to have increased more than for the total economy, with vacancies in professional, scientific and technical services reaching a record high of 47,800 in the first quarter of 2021 (an increase of 12.3% from the year early), and vacancies for computer and information systems professionals increasing by 2,100 (an increase of ~11% from the previous year).

Uncovering the magnitude of the COVID effect on this group is more difficult since vacancy data for the second and third quarter of 2020 is not available. However, job posting data can be used as an imperfect proxy. The data in Figure 15 displays the path of monthly data science related job postings vs other postings from January 2018-March 2021 and normalizes the series to 100 in March 2020 to highlight the disruption to the job market during the pandemic. While postings can contain more than one job position, and coverage of job posting data is more limited than official vacancy data, it is clear than data-science related positions were also negatively impacted by the shutdowns and ensuing recession in the economy. Given these patterns, it would seem to confirm what we have seen in early data – namely that growth related to the adoption and development of computer science and robotic related technologies was impacted by the pandemic.

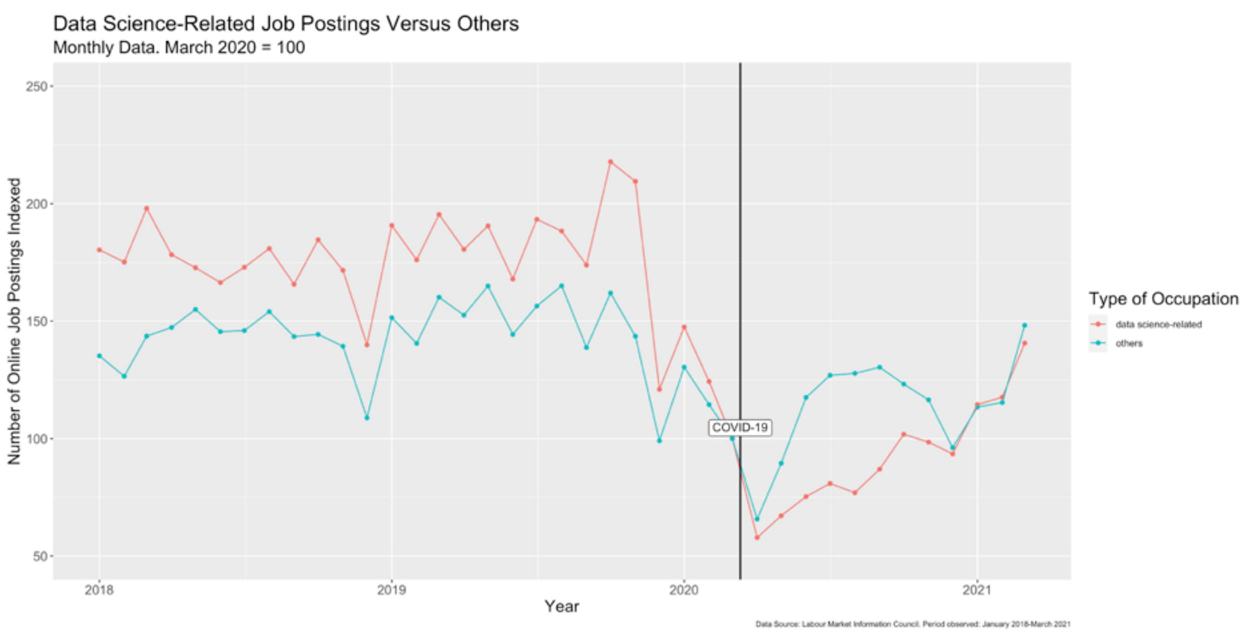


Figure 15: Comparing the number of data science related job postings with others.

4.2.2 Trends Observed from Keyword Searches of Data Sets and Distant Read

Although the data for occupations organized by the NOC system summarized above can provide some insights into the demand for labour by type of job, it is not detailed enough to fully capture the trends for individuals engaged in implementing and developing AI, data science and robotic technologies, and provide evidence on which technologies are viewed by as most disruptive to the labour market going forward. To help supplement the existing statistics and forecasts, we complied statistics from LinkedIn on job titles related to data science, examined trends in media coverage discussing Canada, the labour market and AI, data science, and robotic related technologies, and applied distance reading methods to three bodies of materials: Canadian think tank reports, consulting reports, and the academic and conference papers identified for our systematic review. A summary of notable findings for each of these components are present below

4.2.2.1 Patterns from LinkedIn Job Titles

Based on the notion that workers using the tools are a good measure of commercialization and diffusion of those innovations in the economy, we collected data on the number of individuals with job titles related to data science and AI over time from LinkedIn. Specifically, we merged existing data on the number of people with the title "Data Scientist" over time from June 2017-April 2021 to some indication on the trend's trajectory globally and for Canada where possible. The trends are based on the occurrence of the term data scientist appearing in the current job title on the platform similar to the method used in the Stich (2015) report [33]. The statistics are reported in Table 2 and echo trends seen for the most recent period if the keywords in the title are expanded to include references to AI, deep learning, and machine learning, text analysis, data mining and computer vision.

Table 2: Estimated monthly growth in data scientists on LinkedIn.

	Global	US	Canada
June 2017-June 2018	3.83%	4.29%	n/a
June 2018-Oct 2019	2.81%	2.33%	1.02%
Oct 2019-Nov 2020	1.24%	0.81%	0.68%
Nov 2020- April 2021	4.79%	1.39%	2.40%

Consistent with the pattern seen from our metrics in Section 4.1, there appears to have been a noticeable decline in the growth of data science jobs during the period October 2019 to November 2020. However, since the reopening of the economies, jobs in this area seem to be growing more robustly again. If the most recent trends continue, and additional emergences of COVID cases do not force additional closures or severe economic disruption, these data would suggest that: (1) the pandemic should have only a short run impact on diffusion and adoption of the technologies and (2) the level employment opportunities related to AI and data science will quickly surpass their pre-pandemic levels.

4.2.2.2 Trends from the Media

LinkedIn is not the only alternative source we can derive information from. Here we review the patterns for the subset of English language newspaper articles that discuss Canada, and AI, data science and robotic related technology in Section 4.1.1.4 that also discuss the labour market. We examined the trends for articles making any mention of unemployment, employment, labo(u)r, jobs, employees and workers, as well as for the set of articles focusing specifically on unemployment, layoffs and the loss/decline/decrease/fall/reduction in employment, jobs, and work. Overall, we found that only 41% made mention of these labour market terms, and about 14.6% of those articles mentioned terms related to unemployment or decreased job opportunities.

The industry tag most frequently related to the labour market terms was again the technology sector itself. However, the next most commonly mentioned sectors were the financial service sector, business and consumer services, industrial goods, retail and wholesale trade, and the automotive sector. For this group, it appears that unemployment concerns were most prevalent in the articles related to the financial services sectors with 16.5% of articles from Jan 2015-July 2021 making mention of unemployment or job loss. Articles on the automotive sectors had references approximately 14.8% of the time, while articles in wholesale and retail trade had mentions 13.9% of the time. Of the most widely mentioned groups technology had the lowest rate of mentions at 8.2% with industrial goods and business and consumer services mentioning job loss 9.5% and 10.9% of the time. The ordering in terms of magnitudes of these rates are consistent with the idea that innovations will both create new jobs while potentially destroying others. This is clearest in the technology sector itself where the demand for new product innovations and services related to their commercialization and implementation will work to increase employment in the sector as firms in the economy adopt the technologies. As such, the labour-saving impact on the technology sector that may come about as AI, and automation renders certain routine tasks and jobs obsolete will be offset by the increased employment opportunities in the sector. In contrast, robotic and AI related technologies in the automotive sector will tend to have relatively fewer jobs created by the adoption of these technologies in other sectors but are the sector may shed a considerable number of workers as robotic technologies replace assembly workers and other employment engaged in routine tasks.

Finally, we reviewed the most recent years' articles that mentioned predictions or forecasts for the labour, and those articles mentioning skill shortages or skill gaps. The most mentioned skill shortages referenced were related to digital and data science related skills with the next most common skill gap related to jobs in skilled trades such as electricians. A number of articles suggested policies to deal with the shortages, and labour market disruption. Given that they are similar to ones identified in the systematic literature review and in various think tank and consulting reports, we will summarize them in Section 5. In addition, we found that the predictions or forecasts that were mentioned most frequently in the set appear to be the headline numbers from the World Bank [36], the OCED [6], and Frey & Osborne [12] studies. These, along with specifically identified Canadian centered survey results are summarized in Section 4.2.3 below.

4.2.2.3 Patterns from Distance Reading Analysis of Three Corpuses

A distance reading of the materials helps identify which sectors/industries are most discussed alongside the technological innovations (an indication of interest in adoption and diffusion in the various areas), as well as the frequencies with which different innovations are focused on and which of these are referenced most in conjunction with disruption in the labour market. The patterns were examined for all materials, as well as for the subset of materials that made specific reference to Canada.

As we discuss in Section 4.2.3 a small portion (less than 15%) of the academic literature mentions Canada and even fewer are focused on Canada (only 6%). Therefore, we complemented the systematic review with a distance read analysis of Canadian think tank reports and a series of consulting reports. We used the distance reading methods described in Section 3 to analyse 300 reports from 41 consulting firms and 102 reports from 38 Canadian think tanks as well as the 319 articles resulting from the systematic literature review. Because of our effort to identify Canadian arms of consulting firms (16 firms total out of 41) and Canadian think tanks, there are quite a few more mentions of Canada in these reports. There are 95 references to the United States in the consulting reports, followed by Germany and India with mentions in 67 and 57 consulting reports, respectively. Canada appears in 54 consulting reports, just ahead of China at 52. Figure 16 shows the compares countries by number of consulting reports with mentions.

This compares with the Canadian think tank reports where Canada is mentioned in 89 of them followed by the US, China, Australia, and Germany (mentioned in 53, 17, 16, and 14 reports, respectively). Overall, the patterns of references may give a sense of the countries with which Canada is most often compared from the perspective of the labour market and technological change. However, to probe this question further, we looked at the number of times Canada is mentioned in a report with another country by mention of different technologies. When discussing AI and automation in the consulting reports, Canada is most often mentioned along with the US, the UK, Germany, and Japan. In the Canadian think tank reports, Canada is most often mentioned with the US, Australia, China, and Germany. Interestingly, in the think tank reports, the mentions of Canada together with the US, Australia, and Germany more often include references to automation while the reports with mentions of China more often include discussion of AI. In the systematic literature review articles, Canada is most often mentioned with the US, Germany, Japan, and China and there are many more mentions of robotics technologies in these articles that include Canada and these countries (compared to the think tank and consulting reports). The increased references to China when discussing AI is likely attributable to the significant advances and innovation occurring in the region[33].

In the consulting reports, AI and automation are mentioned in the most reports (161 and 160 reports, respectively) followed by robotics in 122 reports. In the think tank reports and the systematic literature review articles, automation (23 and 272, respectively) and robotics (19 and 264, respectively) are mentioned in the most reports/articles, followed by AI (in 17 reports and 237 articles, respectively). These technologies are most often discussed as being the disruptive to the labour market, expected to create new industries, new jobs, and to make existing jobs redundant. In fact, in our three corpuses, these terms occur very frequently in the same paragraph with the term "employment". For example, "automation" and "employment" occur in the same paragraph over 800 times in the articles from the systematic literature review, nearly 300 times in the consulting reports, and nearly 150 times in the think tank reports.

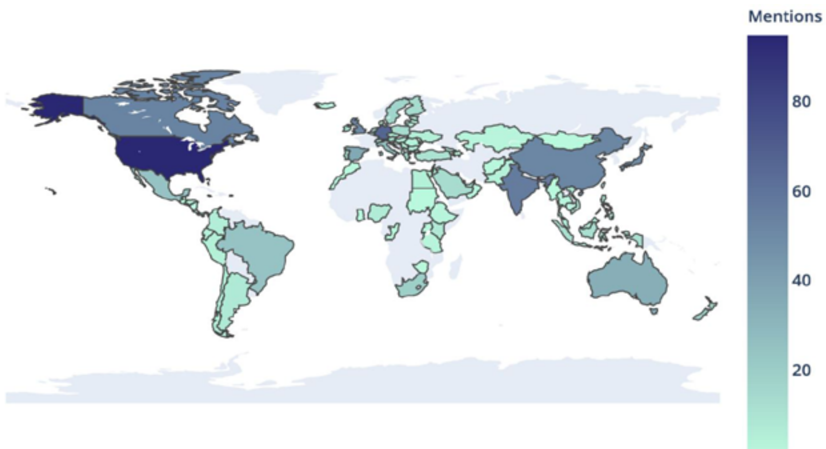


Figure 16: The number of reports that mention each country (darker countries are mentioned in more reports)

A proximity analysis also sheds some light on the magnitude of disruption and frequent policy suggestions. Specifically, the three technologies, AI, automation, and robotics, frequently occur in the same paragraph as the terms "upskilling", "reskilling", or "retraining", further indicating the disruption of these technologies and the need for mechanisms to help workers adapt to the changing environment. In the consulting reports, 488 articles have the term "automation" in the same paragraph as these three terms. In the think tank reports, "automation" and skills terms occur in the same paragraph 72 times and 668 times in the systematic literature review articles.

If we consider the industries most often mentioned in the reports and articles, we find "services" is most often discussed in the consulting reports (193 reports with mentions, followed by "finance, insurance, real-estate, rental, and leasing" with mentions in 132 reports and "manufacturing" with mentions in 126 reports) and think tanks reports (68 reports with mentions, followed by "finance, insurance, real-estate, rental, and leasing" with mentions in 57 reports and "manufacturing" tied with "transportation, information and communications and utilities" with mentions in 54 reports). In the systematic literature review articles, "manufacturing" is most often mentioned (in 254 reports compared to 227 reports with "services" mentioned). Overall, the industries most commonly appearing in these corpora are similar to those we found to be commonly mentioned in the newspaper articles in Sections 4.1.1.4 and 4.2.2.2, and hence paints a consistent picture of areas where significant transformation is underway.

33. See e.g., [4] for evidence that authors affiliated with Chinese institutions currently publish more papers on AI, data science and robotic technologies than authors with US-based affiliations.

4.2.3 Trends Identified through the Systematic Literature Review of Academic Sources

Our systematic literature review identified 319 articles (see Appendix I for a numbered list of articles which are referenced below using the convention [L##]) related to digital technologies and issues of labour and employment. Only 20 of those articles focus on Canada - an indication that more academic peer-reviewed research is needed specifically about the Canadian context. Below we present an overview of the literature and then focus in on a few key articles that present important data and findings.

4.2.3.1 Overview of the Articles

Most of the articles in our dataset of 319 reported on results of a literature review (99 articles) or combined a literature review with another method (8 articles) (see Table 3) . There were 80 articles that analysed data or statistics and another 28 that combined data analysis with another method. Only 59 articles collected new data using a survey or interview. Most of the articles that analysed statistical data, made use of official data sources (see Table 4). This, coupled with the fact that most articles which include forecasts or suggest interventions report on qualitative results (see Table 6 and Table 8) and that those reporting quantitative forecasts or interventions are citing statistics from a few key articles (see Section 4.2.3.2 below) suggest that more quantitative data needs to be collected and made available.

Of those articles that gathered and analysed statistical data, most used official data sources rather than collecting new data and most articles that analysed data focused on AI and robotics technologies (see Table 4). Sources of official data include Department of Labor, Bureau of Labor Statistics and Department of Commerce, Bureau of Economic Analysis, OECD, US Census data, European Statistical System (ESS), the World Bank, World Economic Forum, international professional bodies, country-specific data sources, and others). An example of the use of such data is in [L48] which uses World Economic Forum Data from 2018 to analyse how technological change will cause a shift in work between humans and machines for 75 million jobs and the creation of 133 million new roles. For articles reporting on collecting data, different methods were used such as participant-observation, interviews, surveys, and questionnaires (e.g., [L129, L272, L306]), as well as use of proprietary databases (e.g., [L176]). Many efforts are duplicated in multiple studies, highlighting the need to make data sources available for sharing. Proprietary databases could be more broadly useful if there were techniques for generating realistic synthetic data from data schemas.

Table 3: Evaluating research scope for different study types using article counts.

Study Type	**Research Scope**				
	Industry-level	Firm-level	Country-level	Comparative (cross-country)	Global
Literature review	34	7	30	5	11
Review	21	8	14	8	10
Case study	5	5	10	1	0
Survey or interview	15	12	32	5	4
Data/statistical analysis	36	10	41	31	7

Table 4: Evaluating data source for different digital technologies using article counts.

Digital Technology	**Data Source**		
	Official data (Government source)	Collected data	No data (i.e., reflection, opinion, theme)
AI (ML, DL, NLP, etc.)	50	39	63
Robotics	75	32	40
Big data	21	21	43
IoT	7	11	4
Cloud computing	3	5	3
Other: ICT included	17	7	6

34. In Table 3 to Table 8, counts are not unique. For example, in Table 3, an article that reports on findings from an industry-level literature review and industry-level interviews would be included in the count in both rows of column one.

AI and robotics were also most associated with discussion of the effect on employment in articles in our corpus. Specifically, most of the articles that discussed the effects on employment of AI and robotics technologies, described a negative impact of any kind on employees and many others discussed a negative impact of automation and digitization on employees (see Table 5). While there were some articles that described a positive effect of AI and robotics technologies on employment for employees and industry, fewer articles identified a negative effect on employment for industry. Negative impacts to employees mostly describe job losses and increased inequality (e.g., [L208, L241, L242]). Some articles report that there will be positive impacts on employees including the suggestion that investments in new technologies will positively affect worker wages (e.g., [L120]) and that AI and robotics technologies will augment the work of individuals helping them work safer, more efficiently, and smarter (e.g., [L54, L208, L281]). Examples of how AI and robotics technology will have a positive impact for industry include the fact that efficiency gains through automation will result in an increase in the number of firms and a resulting impact in employment and wages (e.g. [L135]) as well as increased flexibility (e.g., [L106]). Reported negative impacts on industry include increased turnover (e.g., [L93]), overall disruption (e.g., [L30]), and increased competition (e.g., [L159]).

Table 5: Evaluating effect of employment (positive on industry/employees, negative on industry/employees, neutral, or not specified) for different digital technologies and type of digital technology impact using article counts.

Digital Technology	**Type of Digital Technology Impact**	**Effect on Employment**					
		+ve on industry	+ve on employees	-ve on industry	-ve on employees	Neut.	Not spec.
AI (ML, DL, NLP, etc.)	Any	52	58	17	89	8	15
	Automation of tasks/roles	46	54	14	80	7	7
	Digitization/data science	8	7	3	10	2	5
	Training/reskilling/digital literacy	5	9	3	13	2	7
Robotics	Any	56	48	22	77	16	10
	Automation of tasks/roles	53	44	21	70	14	6
	Digitization/data science	6	6	3	8	2	3
	Training/reskilling/digital literacy	5	3	0	7	2	3
Big data	Any	29	31	7	46	4	10
	Automation of tasks/roles	24	28	5	40	3	5
	Digitization/data science	5	5	2	8	2	4
	Training/reskilling/digital literacy	3	9	3	10	1	5
IoT	Any	8	5	2	6	2	3
	Automation of tasks/roles	6	3	1	4	2	2
	Digitization/data science	4	1	1	2	1	2
	Training/reskilling/digital literacy	2	2	1	1	0	1
Cloud computing	Any	4	1	2	5	0	1
	Automation of tasks/roles	1	0	0	3	0	1
	Digitization/data science	3	1	1	1	0	1
	Training/reskilling/digital literacy	0	0	1	0	0	0
Other: ICT included	Any	7	4	7	11	3	4
	Automation of tasks/roles	5	3	7	8	2	4
	Digitization/data science	4	2	3	4	2	3
	Training/reskilling/digital literacy	0	0	0	4	0	0

Table 6 reports on the number of articles that make forecasts about employment in relation to different technologies. Most articles discuss the impact of AI and/or robotics technologies on employment (a total of 169 articles). Many of these articles predict increased underemployment, job redundancy, and a growing numbers of jobs at risk as robots and intelligent machines take over work tasks (e.g. [L98, L256]). Others suggest new jobs will emerge and there will be a shortage of skills needed for those jobs (e.g., [L192, L295]). Some forecast that there will be multiple scenarios (e.g., [L89]) or no particular effect because some jobs will grow, others will decline, and new ones will be created (e.g., [L68, L202]), or that, in the long term there will be new industries and hence more jobs but in the short term, there will be job losses (e.g., [L191]). Predictions also suggest an increase in precarious work and a widening of social and wealth inequality (e.g., [L8, L126, L257, L309]). More of the employment forecasts were qualitative than quantitative in nature; however, some quantitative predictions suggest that 10 million jobs will be replaced by robots (e.g., [L131]). One article reports that the World Bank estimates that 57% of jobs in OECD countries will be lost to automation in the next 20 years, that, in 10 years, 47% of jobs in the US are at risk due to automation, and that the percentage of at-risk jobs in African countries is much greater (e.g., [L194]). Other forecasts report on data showing only 9% of jobs in 21 OECD counties will be automated (e.g., [L215]). Quantitative forecasts include a calculation suggesting job creation will result in a need for 305M jobs between 2020 and 2030 (e.g., [L2]). Another article estimates that 85% of available jobs in 2030 have not yet been created and that half of the workforce will be part of the gig economy by 2027 (e.g., [L152]). These sometimes-contradictory forecasts further indicate the need for more data and more-timely data to be collected, made available and analyzed going forward.

The fact that forecasts indicate there will be new jobs and new industries also suggest that there may be a skills and talent gap. Several of the articles in our corpus discuss the skills and talent gap associated with different technologies (see Table 7), specifically in relation to AI, robotics technologies, and big data.

Table 6: Employment forecasts for different digital technologies using article counts.

Digital Technology	**Inclusion of Employment Forecast**		
	Yes (Quantitative)	Yes (Qualitative)	No
AI (ML, DL, NLP, etc.)	34	52	66
Robotics	34	46	63
Big data	20	30	38
IoT	2	6	11
Cloud computing	0	4	6
Other: ICT included	6	5	17

Table 7: Evaluating skills and talent gap for different digital technologies using article counts.

Digital Technology	**Indication of Skills and Talent Gap**		
	No	Yes	Not mentioned
AI (ML, DL, NLP, etc.)	10	58	86
Robotics	10	52	83
Big data	8	32	49
IoT	0	10	9
Cloud computing	0	5	5
Other: ICT included	2	10	17

4.3 A Review of Key Projections from the Literature

An examination of the predictions and forecasts for the degree of labour market disruption highlight that the vast majority of the estimates cited come from a relatively small set of studies – Frey and Osborne [12], Arntz et al. (OECD 2016) [6] and the World Bank [36] are the most commonly reported estimates. A brief overview reveals that there is a fair bit of disagreement in the estimated magnitudes of future job losses over the next few decades across the studies. Specifically, Frey and Osborne [12] estimated that approximately 47% of US jobs in the US are at risk of being automatable, and the World Bank [36] suggest that about 57% of jobs would be automated in the OECD. The results from Arntz et al [6], on the other hand suggest that share of jobs at risk of automation to be 9%, on average across OECD countries, with the share of jobs at risk in Canada estimated to be about 0.4% higher than the US. As Figure 17 and Figure 18 from [12] and [36] indicate, the risk across jobs for automation varies significantly with occupations requiring creativity, human interaction (e.g., teachers and health care workers), and non-routine task being the least likely to be replace by automation.

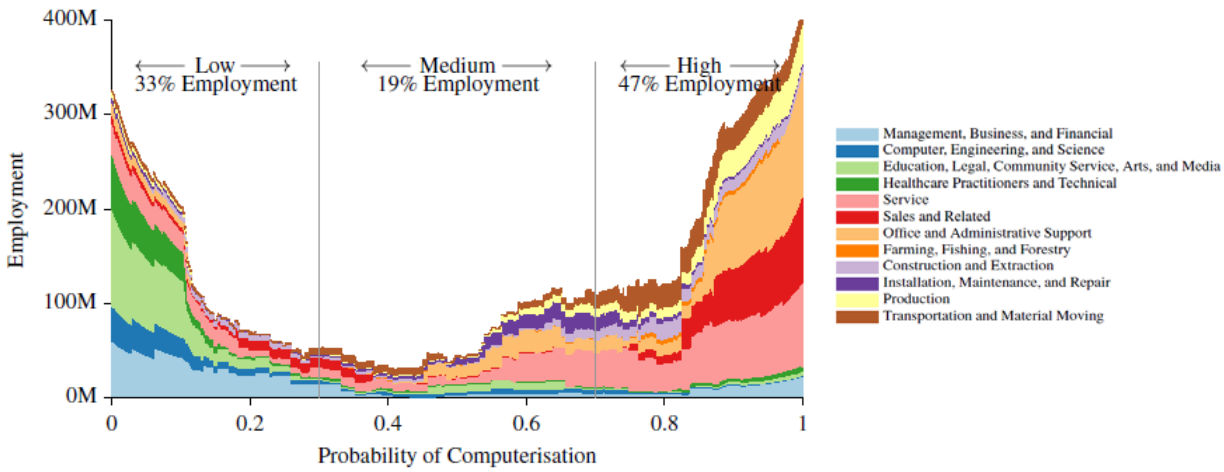
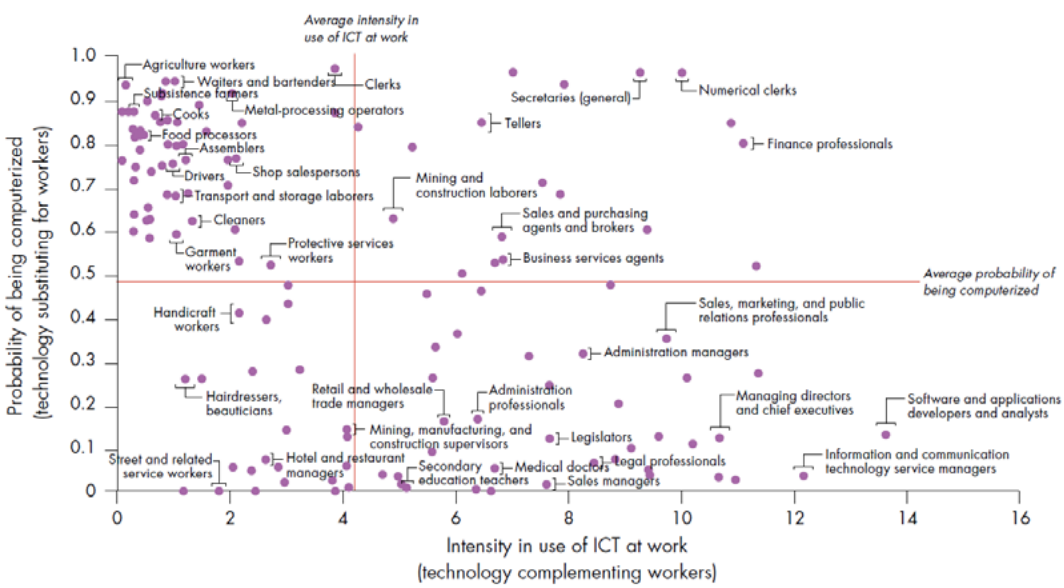


Figure 17: US Employment by risk Category (Source: [12], p 267).

Probability of being computerized and intensity in use of ICT at work, by occupation



Sources: WDR 2016 team, based on STEP household surveys (World Bank, various years) and Frey and Osborne 2013. Data at http://bit.do/WDR2016-Fig2_25.

Note: The probability of being computerized is obtained from Frey and Osborne (2013). ICT intensity is an index between 0 (no use of technology) and 19 (most use of technology). ICT = information and communication technology. The red lines represent the average values of ICT intensity (x-axis) and of computerization (y-axis) across the pooled sample of 10 developing countries with STEP household surveys.

Figure 18: Impact of Technology on Jobs (Source: [36], p. 131).

A few additional Canadian estimates have emerged, although they are less cited. Specifically, a Brookfield study [20] applied Frey and Osborne's method to Canadian data and concluded that 42% of Canadian jobs are at high risk of being affected by automation. Oschinski and Wyonch [24] revisited the calculations from [20] and concluded that the future of job loss was much less bleak for workers in Canada. Specifically, their estimates indicated 35% of Canadian jobs were at higher risk of automation. A McKinsey report indicated that, according to the midpoint adoption scenario, between 23% and 24% of jobs in Canada and the US will be automated by 2030 [22]. However, the two most recent estimates come from Wyonch [37] and Frenette and Frank [11]. Wyonch concluded that the only about 22% of Canadian Jobs are currently at high risk of automation. Frenette and Frank adopt a different approach and conclude the risk may be even lower. Frenette and Frank, point out that the differences in methodology between Frey and Osborne [12] and that of Arntz et al. [6] is that the former takes an occupation-based approach when forming estimates, while the later adopts a more task-based one. As such, they apply the second method in their analysis arguing that the conventional thinking on the topic had evolved so that researchers have moved to adopting the more task-based approach, and they underscore that a finding that a job faces a high automation risk does not necessarily mean that the job will be completely lost – it may simply be transformed. Taking these factors into account, along with the recognition that the process and timing of adoption of new automation are affected by factors such as firms' financial capacity to acquire the technologies, legal constraints (e.g., licensing of certain occupations, regulations, etc.), institutional factors such as union contracts, and consumers' willingness to embrace the changing environment, they conclude that the vast majority of workers in Canada face some risk of job transformation. The estimated risk is at least 10% for 98.2% of the paid workforce with only 10.6% if workers facing a high risk of 70% or more. Their estimates for the share of workers at risk for job transformation by occupation and by industry is displayed in Table 8 below.

Figure 18: Impact of Technology on Jobs (Source: [36], p. 131).

Occupation	Predicted share of workers		**Industry**	Predicted share of workers	
	(%)	Bootstrap Standard Error		(%)	Bootstrap Standard Error
Office support occupations	35.7	6.1	Construction	8.4	3.8
Service supervisors and specialized service occupations	20	7.8	Manufacturing	26.6	3.8
Industrial, electrical and construction trades	19.7	7.9	Wholesale and retail trade	13.4	2.1
Sales representatives and sales persons—wholesale and retail trade	14.7	4.1	Transportation and warehousing	14.5	4.8
Service representatives and other customer and personal services occupations	13.7	4.1	Finance and insurance, real estate and rental and leasing	4.8	1.6
Maintenance and equipment operation trades	13.2	4.8	Professional, scientific and technical services	7.2	2.3
Administrative and financial supervisors and administrative occupations	11.3	2.6	Educational services	4.2	1.5
Technical occupations in health	8.2	3.4	Health care and social assistance	12	2.4

Paraprofessional occupations in legal, social, community and education services	6.4	3.2	Information and cultural industries	2.8	1.4
Technical occupations related to natural and applied sciences	4.4	2	Accommodation and food services	15.4	5.5
Retail sales supervisors and specialized sales occupations	1.8	1.3	Other services	5.6	3.1
Professional occupations in natural and applied sciences	0.9	0.9	Public administration	3.7	1
Professional occupations in business and finance	0.8	0.7			
Specialized middle management occupations 2	0	0			

Source: [11] Technical appendixes A.2, and A.3. Based on data from Statistics Canada, Longitudinal and International Study of Adults, Wave 3 (2016), and an estimated probit fractional response model.

Both Wyonch and Frenette and Frank comment on which groups of Canadians are most likely to be impacted by the automation. Wyonch's findings suggest that men, women and immigrants face a similar risk from automation and that the differences seen are not large enough to warrant targeted pre-emptive policies for these groups. Instead, she argues that the inequality effects could be indirectly addressed though education and labour market policies designed to target inequality more generally (including income and employment support). The analysis does, however, suggest that Black and Indigenous people may suffer worse outcomes from automation relative to the Canadian average. Frenette and Frank also do not find significant differences in the risk of job transformation on the basis of gender, immigration status, having a disability or being unionized. However, they identify heightened risks for older workers (age 55 or above), and younger workers (aged less than 24), as well as workers who had no postsecondary or postsecondary credentials in certain fields, and/or had low literacy or numeracy proficiency.

5. Implications

We now turn to a discussion of our third theme - policies that have been identified in the literature that may assist Canadian firms' ability to compete internationally, promote wide-spread economic growth in Canada, support the evolving labour needs of firms over the years to come and help support displaced workers during the transition to the new economy. The results are informed from the review of recent news identified in Section 4.2.2.2, and the combination of results from our Distant Read analysis and Systematic Literature Review.

5.1. Views on recommended Policies and interventions

Table 9 summarizes information on the coverage of policy interventions discussed in the corpora of academic literature and conference proceedings in our systematic literature review. As the table highlights, most interventions discussed are qualitative in nature, and the number of articles that provide policy recommendations is relatively small. The number of papers that focus on Canada and makes policy recommendations based on analysis that includes any data collected post 2017 reduces the set to 2 papers [L44] and [L77]. As a result, it would appear that there is a need for more rigorous peer reviewed studies that identify interventions to support a transition for workers, firms, and industries in the face of technological change in the Canadian context.

Digital Technology	Mention of Intervention		
	Yes (Quantitative)	Yes (Qualitative)	No/Other Commentary
AI (ML, DL, NLP, etc.)	1	53	99
Robotics	1	39	103
Big data	0	36	53
IoT	0	7	12
Cloud computing	1	1	8
Other: ICT included	1	7	21

Table 9: Evaluating interventions (e.g., policy, training, regulations) for different digital technologies using article counts.

Some of the policy recommendations from the most recent articles in our sample are summarized here to highlight the most recent views and suggestions. Sutherland [L286] suggests that a supply of skills can be ensured through basic and higher education, continuing professional development, supporting relocation, and retraining programs for those whose jobs are made redundant from automation. Other recommendations, from papers such as [L152] include using community and technical colleges for retraining programs that can target local and under-serviced communities as well as encouraging collaboration and professional development opportunities. Retraining programs and job creation programs are also highlighted, as well as increased infrastructure including broadband internet [L314]. The need for high-speed internet access for all and a growing digital divide was painfully evident during the pandemic [19]. Therefore, making broadband internet accessible across Canada is an imperative pre- and post-pandemic for a digital economy. Social innovation is another intervention recommended for governments which includes establishing partnerships among public institutions, private companies, and NGOs as well as increasing systems for life-long learning [L158]. Further, both formal and informal training opportunities should be available (e.g., [L58]) provided by the workplace (e.g., [L306]).

In addition to the recommendations above, the two most recent papers in the systematic literature review focusing on Canada provides some specific recommendations for domestic policies. Blit [L44] indicated that the $58 million Ontario Investment for Adoption of Digital Technologies is a good initiative that can hopefully pave the way for other similar initiatives in the future, but that this should be complemented by a development of programs that help mobilize the expertise in AI and robotics the higher education sector for the benefit of Canadian businesses. Moreover, he argued that the broad-based business supports be replaced by smaller more targeted interventions on an industry-by-industry bases, and that Canada could consider a guaranteed basic income that would replace the programs like the Canada Emergency Response Benefit (CERB). Complementary suggestions for Canadian policy makers can be found in the Cukier's litera-

ture review [L77]. Specifically, Cukier reviews the benefits to social innovation in work integrated learning which include cross-sectoral collaborations between post-secondary education organizations and employers that are designed to provide work-integrated learning opportunities with the expressed intent of reducing skills gaps. This suggestion is based on work finding that students who participate in work-integrated learning (e.g., through a co-op or internship) earn a labour market premium. Examples that could be examined in a Canadian context include outcomes for Ryerson University's Advanced Digital and Professional training Programme as well as outcomes for students engaged in Mitacs programs. In addition, Canada policy makers may consider further developing/supporting fine-tuned technology-enabled talent matching platforms such as the MAGNET platform (a joint partnership between Ryerson University and the Ontario Chamber of Commerce) to help to overcome the skills gaps and discrimination in the recruitment process.
Many of the recent news articles discussing policies that may help alleviate skill gaps and minimize the costs for firms and displaced workers echoed these themes of re-skilling and upskilling programs (including IBM's Tech Re-entry program to promote more gender diversity in STEM roles) and suggested encouraging uptake rates for micro-credential courses. These are promising avenues since Yu's July 26, 2021 article on skill shortages indicates that a May 2021 survey suggested that 36% of Canadian Firms had not considered reskilling or upskilling programs. [38]. Moreover, it would be beneficial to further advertise programs for workers such as the Second Career strategy[35] launched by the Ontario Ministry of Training, Colleges and Universities pays for the training or education that Ontarians require to get a better job, and widely pubilized the fact that the Ontario Student Assistance Program (OSAP) currently provides financial support to students accessing approved micro-credentials though its program. Finally, altering immigration and reducing costs to foreign workers in obtaining required visas and acquiring certification (where necessary) when they have skills to fill jobs in areas with a shortage of skilled labour remains a promising avenue to deal with the short run imbalances that may arise.

5.2 Information creation and access

In addition to identifying policy related to the adoption of AI and data science technologies in the literature, the review clearly identifies a number of existing data gaps that can be addressed by Government initiatives. For example, many datasets available from Statistics Canada are generally released at levels of aggregation that make it difficult to identify and track the specific sectors that are experiencing issues with workers' skill levels and recruiting. Finer levels of disaggregation would help in this regard, as would more clearly defined statistics that specifically track the portion of job vacancies, employment, R&D behaviour, and investment in the sectors of the economy related to the digital economy. The ongoing work by Statistics Canada on the size of the digital economy is a good start, but more work should be done on this front with a particular focus on expanding disaggregate statistics on vacancy rates, job postings and evolving skill requirements. These data could be complemented with job posting data, such as that available through LMIC. Even though job posting data have some well-known shortcomings as measures of true vacancies, a concerted effort to increase the available data more widely, and the ability to use data mining techniques to identify changing skill requirements over time in a timely fashion could play a crucial role in early detection of pain points, skill shortages and types of workers who will likely be effected as the new AI, data science and robotic related technologies are adopted by firms in different sectors. Currently, the time lags between data collection and official data releases hinders efforts by policy makers to respond to evolving issues quickly. This issue was clearly demonstrated during the pandemic as economists and policy makers needed to turn to less traditional sources of data to track the ongoing shifts in economic activity. However, even in less drastic times, the further development of more real time indicators on technical adoption and its impact on workers will improve outcomes.

Other initiatives to improve available data could include ongoing mini-surveys to yield more timely information on use of new technologies and the diversity of the workforce employed in jobs utilizing the tools on the job, and the development of real time indicators based on textual analysis and distance reading to track developments in real time from newspapers, and corporate filings. Further, it may be useful to development and maintain certain patent application or trademark counts using anonymized and aggregated data in areas related to rapid tech change like ML/ Data science, AI and robotic technologies. As we argued above, this would give researchers and policy makers an early indicator of disruption on the innovation front, while still protecting the intellectual property contained in the applications due to the aggregation and publication of the counts.

35. https://www.ontario.ca/page/second-career

6. Conclusions

To answer our questions, we synthesized data from a variety of sources and presented findings organized by theme. The first theme focused on the shifting landscape for firms and trends in adoption, diffusion, and innovation of AI and data science related technologies in Canada pre- and post-COVID-19. The second theme addressed the effects of technological change on the labour market, identifying changes in employment opportunities, skill gaps, and job loss in Canada. The third theme concentrated on policies that may assist Canadian firms and encourage economic growth in Canada as we transition to the new economy.

From all of the pieces of evidence available, it would appear that prior to the pandemic, the commercialization and diffusion of AI, data science and robotic related technologies was growing at a rapid pace. However, with the onset of the pandemic, the lockdowns and restrictions caused a severe recession that appears to have delayed investment and adoption plans for these technologies for many firms in the economy and slowed the pace of related innovation in these areas. We identified issues with the availability of data to predict the future path of diffusion of both commercialized, and future commercializable innovations. Future research is needed to understand the long-term impacts of the pandemic on data science innovation, adoption, and diffusion but this will require that disaggregated and up-to-date data be collected and made available. Throughout our synthesis of data sources, we found a lack of available data on these issues, specifically with respect to Canada, indicating that future research into incentives for data sharing and the development of methods for generating realistic synthetic data from data schemas of proprietary databases is needed.

The slowdown in commercialization and innovation likely means that the timing of labour market disruptions and the possible emergence of skill gaps related to the adoption of the associated technologies will occur at least a few years later than originally forecast. However, if the most recent trends continue, and future COVID-19 waves do not force additional closures or severe economic disruption, these data would suggest that employment opportunities related to AI and data science will quickly surpass their pre-pandemic levels. As a result, there is a need for more peer-reviewed studies that identify interventions that will support the transition for workers, firms, and industries and ensure infrastructures and policies are in place to facilitate the growth expected post-pandemic – especially in the Canadian context. Additionally, given that there remains significant variation in the forecasts on how many jobs will be lost and/or significantly transformed, more emphasis should be placed on encouraging the development of high-quality data that can used by researchers and policy makers to better track the evolving trends and assess the need for labour market intervention and support for Canadian firms and workers.

Another area for future research is diversity and equitable access. Studies suggest Black and Indigenous people may suffer worse outcomes from automation relative to the Canadian average [37]. Women are under-represented in tech jobs in general but there is even less representation of women in AI careers. One study found that only 12% of leading machine learning researchers were women compared to approximately 20% women in general areas of technology work [32]. Recent studies indicate that the pandemic has had a stronger impact on the careers of women (especially those with young children) than men which might further affect gender diversity in AI and data science [18]. We found conflicting predictions for women's participation in our analysis, some suggestion that women's jobs will be less affected by automation then men's (e.g., [L72]) and other saying women will be more affected by technological change (e.g., [L136]). Future research is needed to better understand the impact of technological change and the pandemic on diversity and to better design interventions to enable full participation in the digital economy.

7. Knowledge Mobilization Activities

In order to share our findings with policy makers, academics, and the public, we have undertaken several knowledge mobilization activities to date. At the beginning of the project, we launched our website[36] at the University of Toronto and created both a Twitter[37] account and a LinkedIn[38] page to promote the findings of the project as they have become available. We have been posting material to our site since it was unveiled in February 2021. The material includes a number of trends and snapshots and mini-reports related to the project themes discussed in Section 4, as well as copies of the Twitter feed, links to related content, and announcements about events. The current report has also been archived and made available for download on the site[39] .

As results have been compiled, we have shared announcements on our Twitter account and LinkedIn page and we have disseminated the findings through a number of additional channels and activities. First, we shared preliminary results with policy makers by participating in a panel discussion on the future of the digital economy after Covid. Prof. Michelle Alexopoulos delivered the comments at the Bank of Canada's 2021 Fellowship Learning exchange on May 5th, 2021. We have also had one paper accepted for publication and presentation at the CASCON Conference in Toronto [4] and another paper submitted to the IEEE International Symposium on Technology and Society (ISTAS) [5] (both conferences will be held online in the Fall of 2021). Finally, we have submitted a proposal to organize a workshop at CASCON 2021 where we will present the findings of the report and where panelists (chosen from academia, the private sector, and policy makers) will lead a discussion on the topics and suggestions raised by the review. We intend to continue to add content to the website over the following months to further the discussion and the community outreach.

36. https://futurejobscanada.economics.utoronto.ca/
37. https://twitter.com/futureJobsCan
38. https://www.linkedin.com/company/future-jobs-canada
39. https://futurejobscanada.economics.utoronto.ca/final-report/

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Appendices

APPENDIX A: Systematic Literature Review Methodological Details

A.1 Screening Guidance Tables

<table>
<tr><td colspan="2">Does this study focus on digital technologies?</td></tr>
<tr><td>INCLUDE</td><td>EXCLUDE</td></tr>
<tr><td>
<table>
<tr><td>Include these:</td><td>Described as:

Digital
Automated
Connected
Robotic
Modernized
Technologies
Technological advancements
High technology/hig h tech
Machines
Computers Equipment
Robots</td></tr>
</table>
</td><td>Exclude articles that:
With mention of analog technologies (ex. tape players, record players, photocopiers)
Are not related to artificial intelligence, data science technologies</td></tr>
</table>

<table>
<tr><td colspan="2">Does this focus on the nature of work?</td></tr>
<tr><td>INCLUDE</td><td>EXCLUDE</td></tr>
<tr><td>
<table>
<tr><td>

Employment
Unemployment
Jobs
Labo*r
Work

Focusing on changes in the labour market, industry employment
</td><td>
Nature of Work (*covers all industries; doesn’t need to be associated w/ specific industry)

Hiring
Occupation
Profession
Position
Vocation
Post
Career
Designation
Undertaking
Project
Workforce
Worker
Wages
Working Conditions
Compensation
Skills/Training

Type of Work

Full-time
Part-time
Commission
Contract
Appointment
Consulting
Seasonal

Changes to Labour Market
(-) Changes to Employment

Discharge

</td></tr>
</table>
</td><td>

Articles that examine digital technologies unrelated to work
Ex. leisure, personal projects, volunteering, unpaid internship
Articles that do not describe a change in the nature of work, i.e., static (ex. job description)
What about digital labour (web development, blogging, YouTube video creator, content creator) and the digital economy?
Digital labour that does not relate to AI (blogging, YouTube video creator, content creator)

</td></tr>
</table>

	• Dismissal • Fire • Removal • Severance • Demotion • Furlough • Layoff • ~~Retirement~~ • Turnover (+) Changes to Employment • Increase in demand • Job openings • Job opportunities • Job postings • Vacancies* (postings and opps.) • Professional development (ex. Career fairs,	

<table>
<tr><th colspan="2">PUBLICATION TYPE – Is this the right publication type?</th></tr>
<tr><td>INCLUDE</td><td>EXCLUDE</td></tr>
<tr><td>Publications should be in text format. Must be published between 2015 – 2021.

Grey Literature
Conference abstracts
Conference proceedings
Organization reports *distant reading
Theses, dissertations
Government reports
Government funded policy briefs/statements
Pre-prints
Consulting and Technical reports
NGO and think tank reports
Official press releases (from firms) *will likely exclude those not on the Stock Exchange
Scholarly Database
Environmental scans
Case studies
Case reports
Research articles
Monographs
Book chapters
Book reviews
Editorials, letters to the editor, commentaries
Opinion pieces
Knowledge syntheses (literature review)</td><td>Multimedia (videos, audio recordings)
Social media
Personal blogs
Community forums
Organizational pages
Newspapers? *separately, distant reading
Magazines
Encyclopedia
Anything published prior to 2015.</td></tr>
</table>

AND CONCEPT Does this focus on transformation? <innovation and adoption>		
INCLUDE		**EXCLUDE**
• Innovation • Adoption Economic Processes • Distribution • Consumption • Production • Extraction Focusing on the industry. (KL here: I think “the firm” but MA will know better) - Industry trends - Individual Firms *Linked to future/forecasting/prediction	• Growth • Development • Long term trends • Short term trends • Immediate trends • Transformation • Boom • Expansion • Improvement? • Progress • Proliferation • Diversification • Uptrend • Investment • R & D • Changes to Employees Intake? • Diffusion • Disruption • Reduction • Decline • Diminish • Loss • Depression • Shrink • Depreciation Future: - Future - Forecasting - Prediction	• Exclude articles where there is no indication of changes, investments, future forecasting or predictions • What if the industry was already based online like social media? Or is it like the industry has to be shifted online to be ‘transformed’?

LANGUAGE – Is this study in English?	
INCLUDE	**EXCLUDE**
Studies written in English only.	Studies written in any other language that is not English.

A.2 List of Databases

Database	Limited to
Engineering Village	• Compendex • Inspec • GEOBASE
ProQuest	• ABI/Inform Collection (1971–Current) • Applied Social Sciences Index & Abstracts (ASSIA) • Canadian Business & Current Affairs Database • Canadian Research Index • Coronavirus Research Database • eBooks Central • ERIC • International Bibliography of the Social Sciences (IBSS) • Library & Information Science Abstracts (LISA) • PAIS Index (1914–Current) • Sociological Abstracts • Worldwide Political Science Abstracts
EBSCOHost	• Alternative Press Index • Business Source Premier • EconLit • eBook Collection • Education Source • GreenFILE • Humanities International Index • Left Index • Library, Information Science & Technology Abstracts
Scopus*	• Alternative Press Index • Business Source Premier • EconLit • eBook Collection • Education Source • GreenFILE • Humanities International Index • Left Index • Library, Information Science & Technology Abstracts
Web of Science	• Science Citation Index Expanded (1990–Present) • Social Sciences Citation Index (1900–Present) • Arts & Humanities Citation Index (1975–Present) • Conference Proceedings Citation Index–Science (1990–Present) • Conference Proceedings Citation Index–Social Science & Humanities (1990–Present) • Book Citation Index–Science (2005–Present) • Book Citation Index–Social Sciences & Humanities (2005–Present) • Emerging Sources Citation Index (2005–Present)

*Searched by subject areas

A.3 Search Strategies

Engineering Village
Date Retrieved: March 19, 2021

(((((({learning (artificial intelligence)} or {cloud computing} or {artificial intelligence} or {data mining} or {big data} or {machine learning} or {predictive analytics} or {Internet of Things} or {data analysis} or {deep learning} or {neutral nets} or {feature extraction} or {neural networks} or {learning algorithms} or {support vector machines} or {automation} or {computer vision} or {remote sensing} or {robotics} or {data analytics} or {heuristic algorithms} or {intelligent computing} or {recommender systems} or {data science} or {clustering algorithms} or {data acquisition} or {advanced analytics} or {convolutional neural networks} or {mobile computing} or {intelligent systems} or {mobile robots} or {logistic regression} or {multilayer neural networks} or {virtual reality} or {deep neural networks} or {natural language processing systems} or {natural language processing} or {computational linguistics} or {speech recognition} or {text analysis} or {pattern classification} or {learning systems} or {text mining} or {text processing} or {sentiment analysis} or {speech processing} or {pattern clustering} or {speech synthesis} or {ontologies (artificial intelligence} or {recurrent neural nets} or {industrial robots} or {robots} or {robot applications} or {computer aided manufacturing} or {intelligent robots} or {robots, industrial} or {agricultural robots} or {medical robotics} or {service robots}) AND ({employment} or {personnel} or {labour resources} or {labor resources} or {personnel training} or {unemployment} or {recruitment} or {labor market} or {labour market} or {labor supply} or {labour supply} or {skilled labor} or {skilled labour} or {industrial relations} or {industrial economics}) AND ({forecasting} or {economic and social effects} or {productivity} or {investments} or {investment} or {innovation management} or {social aspects of automation} or {socio-economic effects} or {technological change} or {technical change} or {innovation} or {investments} or {diffusion} or {research and development management} or {industrial research} or {organizational aspects} or {innovation management} or {technology transfer} or {technological development} or {research and development} or {technology adoption} or {technology diffusion} or {technological forecasting} or {factory automation})) WN CV))) AND (({english} WN LA) AND ((2021 OR 2020 OR 2019 OR 2018 OR 2017 OR 2016 OR 2015) WN YR)))

ProQuest
Date Retrieved: March 22, 2021

ab("cloud comput[*3]" OR artificial intelligence? OR data min[*3] OR "big data" OR "machine learn[*3]" OR "predictive analytic?" OR "Internet of Things" OR IoT OR "data analysis" OR "deep learn[*3]" OR "neutral net?" OR feature? NEAR/3 extract[*4] OR "neural network?" OR "learning algorithm?" OR "support vector machine?" OR automat[*3] OR "computer vision?" OR "remote sens[*3]" OR robot[*3] OR "data analytic?" OR "heuristic algorithm?" OR intelligent NEAR/3 comput[*3] OR "recommender system?" OR "data science?" OR "clustering algorithm?" OR "data acquisition?" OR "advanced analytic?" OR "convolutional neural network?" OR "mobile comput[*3]" OR "intelligent system?" OR "mobile robot?" OR "logistic regression" OR "multilayer neural network?" OR "virtual reality" OR "deep neural network?" OR "natural language processing system?" OR "natural language process[*3]" OR "computational linguistic?" OR "speech recognit[*3]" OR "text analysis" OR "pattern classificat[*3]" OR "learning system?" OR "text min[*3]" OR "text process[*3]" OR "sentiment analysis" OR "speech process[*3]" OR "pattern cluster[*3]" OR "speech synthesis" OR "artificial intelligence ontolog[*3]" OR "recurrent neural net?" OR "industrial robot?" OR "robot?" OR "robot application?" OR "computer aided manufactur[*3]" OR "intelligent robot?" OR "industrial robot?" OR "agricultural robot[*3]" OR "medical robot[*3]" OR "service robot?") AND ab(employ[*4] OR personnel OR "labo?r resource?" OR "personnel training" OR unemploy[*4] OR recruit[*4] OR "labo?r market" OR "labo?r suppl[*3]" OR "skilled labo?r" OR "industrial relation?" OR "industrial economic?") AND ab(forecast[*3] OR "economic effect?" OR "social effect?" OR "economic and social effect?" OR "productivity" OR investment? OR "innovation management?" OR "social aspects of automation?" OR "social aspect of automation?" OR "socio-economic effect?" OR "socioeconomic effect?" OR "technological change?" OR "technical change?" OR innovation? OR diffusion? OR "research and development management" OR "R and D management" OR "industrial research" OR "organizational aspect?" OR "innovation management" OR "technology transfer?" OR "technological development?" OR "research and development" OR "technology adoption?" OR "technology diffusion?" OR "technological forecast[*3]" OR "factory automat[*4]")

EBSCOHost
Date Retrieved: March 19, 2021

AB (“cloud comput*3” or artificial intelligence# or data min*3 or “big data” or “machine learn*3” or “predictive analytic#” or “Internet of Things” or IoT or “data analysis” or “deep learn*3” or “neutral net#” or feature# N3 extract*4 or “neural network#” or “learning algorithm#” or “support vector machine#” or automat*3 or “computer vision#” or “remote sens*3” or robot*3 or “data analytic#” or “heuristic algorithm#” or intelligent N3 comput*3 or “recommender system#” or “data science#” or “clustering algorithm#” or “data acquisition#” or “advanced analytic#” or “convolutional neural network#” or “mobile comput*3” or “intelligent system#” or “mobile robot#” or “logistic regression” or “multilayer neural network#” or “virtual reality” or “deep neural network#” or “natural language processing system#” or “natural language process*3” or “computational linguistic#” or “speech recognit*3” or “text analysis” or “pattern classificat*3” or “learning system#” or “text min*3” or “text process*3” or “sentiment analysis” or “speech process*3” or “pattern cluster*3” or “speech synthesis” or “artificial intelligence ontolog*3” or “recurrent neural net#” or “industrial robot#” or “robot#” or “robot application?” or “computer aided manufactur*3” or “intelligent robot#” or “industrial robot#” or “agricultural robot*3” or “medical robot*3” or “service robot#”) AND AB (employ*4 or personnel or “labo#r resource#” or “personnel training” or unemploy*4 or recruit*4 or “labo#r market” or “labo#r suppl*3” or “skilled labo#r” or “industrial relation#” or “industrial economic#”) AND AB (forecast*3 or “economic effect#” or “social effect#” or “economic and social effect#” or “productivity” or investment# or “innovation management#” or “social aspects of automation#” or “social aspect of automation#” or “socio-economic effect#” or “socioeconomic effect#” or “technological change#” or “technical change#” or innovation# or diffusion# or “research and development management” or “R and D management” or “industrial research” or “organizational aspect#” or “innovation management” or “technology transfer#” or “technological development#” or “research and development” or “technology adoption#” or “technology diffusion#” or “technological forecast*3” or “factory automat*4”)

Scopus
Date Retrieved: March 19, 2021

TITLE-ABS (({cloud comput*} OR artificial AND intelligence OR data AND min* OR {big data} OR {machine learn*} OR {predictive analytic} OR {predictive analytics} OR {Internet of Things} OR iot OR {data analysis} OR {deep learn*} OR {neutral net} OR {neutral nets} OR (feature W/3 extract*) OR {neural network} OR {neural networks} OR {learning algorithm} OR {learning algorithms} OR {support vector machine} OR {support vector machines} OR automat* OR {computer vision} OR {computer visions} OR {remote sens*} OR robot* OR {data analytic} OR {data analytics} OR {heuristic algorithm} OR {heuristic algorithms} OR (intelligent W/3 comput*) OR {recommender system} OR {recommender systems} OR {data science} OR {data sciences} OR {clustering algorithm} OR {clustering algorithms} OR {data acquisition} OR {data acquisitions} OR {advanced analytic} OR {advanced analytics} OR {convolutional neural network} OR {convolutional neural networks} OR {mobile comput*} OR {intelligent system} OR {intelligent systems} OR {mobile robots} OR {mobile robot} OR {mobile robots} OR {logistic regression} OR {multilayer neural network} OR {multilayer neural networks} OR {virtual reality} OR {deep neural network} OR {deep neural networks} OR {natural language processing system} OR {natural language processing systems} OR {natural language process*} OR {computational linguistic} OR {computational linguistics} OR {speech recognit*} OR {text analysis} OR {pattern classificat*} OR {learning system} OR {learning systems} OR {text min*} OR {text process*} OR {sentiment analysis} OR {speech process*} OR {pattern cluster*} OR {speech synthesis} OR {artificial intelligence ontolog*} OR {recurrent neural net} OR {recurrent neural nets} OR {industrial robot} OR {robot applications} OR robot OR {robot application} OR {robot applications} OR {computer aided manufactur*} OR {intelligent robot} OR {intelligent robots} OR {industrial robot} OR {service robots} OR {agricultural robot*} OR {medical robot*} OR {service robot} OR {service robots}) AND (employ* OR personnel OR {labo?r resource} OR {labo?r resources} OR {personnel training} OR unemploy* OR recruit* OR {labo?r market} OR {labo?r suppl*} OR {skilled labo?r} OR {industrial relation} OR {industrial relations} OR {industrial economic} OR {industrial economics}) AND (forecast* OR {economic effect} OR {economic effects} OR {social effect} OR {social effects} OR {economic and social effect} OR {economic and social effects} OR {productivity} OR investment OR {innovation management} OR {innovation managements} OR {social aspects of automation} OR {social aspects of automations} OR {social aspect of automation} OR {social aspect of automations} OR {socio-economic effect} OR {socio-economic effects} OR {socioeconomic effect} OR {socioeconomic effects} OR {technological change} OR {technological changes} OR {technical change} OR {technical changes} OR innovation OR diffusion OR {research and development management} OR {R and D management} OR {industrial research} OR {organizational aspect} OR {organizational aspects} OR {innovation management} OR {technology transfer} OR {technology transfers} OR {technological development} OR {technological developments} OR {research and development} OR {technology adoption} OR {technology adoptions} OR {technology diffusion} OR {technology diffusions} OR {technological forecast*} OR {factory automat*})) AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ch") OR LIMIT-TO (DOCTYPE , "re") OR LIMIT-TO (DOCTYPE , "cr") OR LIMIT-TO (DOCTYPE , "bk")) AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "ECON")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p") OR LIMIT-TO (SRCTYPE , "k") OR LIMIT-TO (SRCTYPE , "b") OR LIMIT-TO (SRCTYPE , "d"))

Web of Science
Date Retrieved: March 19, 2021

(AB=(("cloud comput*" or artificial intelligence$ or data min* or "big data" or "machine learn*" or "predictive analytic$" or "Internet of Things" or IoT or "data analysis" or "deep learn*" or "neutral net$" or feature$ NEAR/3 extract* or "neural network$" or "learning algorithm$" or "support vector machine$" or automat* or "computer vision$" or "remote sens*" or robot* or "data analytic$" or "heuristic algorithm$" or intelligent NEAR/3 comput* or "recommender system$" or "data science$" or "clustering algorithm$" or "data acquisition$" or "advanced analytic$" or "convolutional neural network$" or "mobile comput*" or "intelligent system$" or "mobile robot$" or "logistic regression" or "multilayer neural network$" or "virtual reality" or "deep neural network$" or "natural language processing system$" or "natural language process*" or "computational linguistic$" or "speech recognit*" or "text analysis" or "pattern classificat*" or "learning system$" or "text min*" or "text process*" or "sentiment analysis" or "speech process*" or "pattern cluster*" or "speech synthesis" or "artificial intelligence ontolog*" or "recurrent neural net$" or "industrial robot$" or "robot$" or "robot application$" or "computer aided manufactur*" or "intelligent robot$" or "industrial robot$" or "agricultural robot*" or "medical robot*" or "service robot$") AND (employ* or personnel or "labo?r resource$" or "personnel training" or unemploy* or recruit* or "labo?r market" or "labo?r suppl*" or "skilled labo?r" or "industrial relation$" or "industrial economic$") AND (forecast* or "economic effect$" or "social effect$" or "economic and social effect$" or "productivity" or investment$ or "innovation management$" or "social aspects of automation$" or "social aspect of automation$" or "socio-economic effect$" or "socioeconomic effect$" or "technological change$" or "technical change$" or innovation$ or diffusion$ or "research and development management" or "R and D management" or "industrial research" or "organizational aspect$" or "innovation management" or "technology transfer$" or "technological development$" or "research and development" or "technology adoption$" or "technology diffusion$" or "technological forecast*" or "factory automat*"))) AND LANGUAGE: (English)

Refined by: [excluding] DOCUMENT TYPES: (RETRACTED PUBLICATION)

Timespan: 2015-2021. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI.

A.4 Applying Weights to Keywords

Inclusion work-related terms

1. employment: 2
2. unemployment: 1
3. Unemployed:1
4. labo(u)r(s): 2
5. labo(u)r market: 2
6. work(s): 0.25
7. future of (work(s)|job(s)|employment(s)): 2
8. emerging (work(s)|job(s)|employment(s)): 2
9. new (work(s)|job(s)|employment(s)): 2
10. re(-)skill(s|ing|ment): 2,
11. up(-)skill(s|ing|ment): 2
12. job(s): 2
13. personnel training(s): 2
14. (fourth|4th) industrial revolution: 0.5
15. industry 4.0: 0.5
16. skill(s): 1
17. workforce: 1
18. occupation(s): 1
19. hiring: 1
20. profession(s): 1
21. position(s): 1
22. vocation(s): 1
23. career(s): 1
24. wage(s): 1
25. working.condition(s): 1
26. compensation: 1
27. production: 1,
28. productivity: 0.5,
29. worker(s): 0.5
30. full(-)time: 0.5
31. part(-)time: 0.5
32. commission(s): 0.5
33. contract(s): 0.5
34. appointment(s): 0.5
35. consulting: 0.5
36. seasonal: 0.5
37. discharge: 0.5
38. dismissal: 0.5
39. fire: 0.5
40. removal: 0.5
41. severance: 0.5
42. demotion: 0.5
43. furlough: 0.5
44. layoff: 0.5
45. retirement: 0.5
46. turnover: 0.5
47. increase in demand(s): 0.5
48. job(s).opening(s): 0.5
49. job(s).opportunit(y|ies): 0.5
50. job(s).posting(s): 0.5
51. vacanc(y|ies): 0.5
52. professional development: 0.5

Inclusion technology-related terms

1. artificial intelligence: 0.5
2. computer vision(s): 0.5
3. speech recognition(s): 0.5
4. machine learning: 0.5
5. image recognition(s): 0.5
6. intelligence.system(s): 0.5
7. deep learning: 0.5
8. neural network(s): 0.5
9. facial recognition(s): 0.5
10. virtual assistant(s): 0.5
11. reinforcement learning: 0.5
12. natural language processing: 0.5
13. face recognition(s): 0.5
14. autonomous vehicle(s): 0.5
15. predictive analytic(s): 0.5
16. self-driving: 0.5
17. data scientist(s): 0.5
18. data science: 0.5
19. text analytic(s): 0.5
20. data analytic(s): 0.5
21. data mining: 0.5
22. automat(e|ed|ic|ion): 0.5
23. robot(s): 0.5
24. digital: 0.5
25. technological.(change|advancement): 0.5
26. technology.(change|advancement): 0.5
27. innovation(s): 0.5
28. machine(s): 0.25
29. technolog: 0.25
30. connected: 0.25
31. modernized: 0.25
32. transformation(s): 0.25
33. high.tech(nology):0.25
34. computer equipment(s): 0.25

Exclusion terms

1. tape_player(s): -1,
2. record_player(s): -1,
3. photocopier(s): -1,
4. leisure(s): -1,
5. personal_project(s): -1,
6. volunteer(s|ing): -1,
7. unpaid internship(s): -1,
8. cloud job(s): -2,
9. job(s) execution: -2

A.5 Seven-Step Filtering Process

Step 1: Keyword(s) in abstract

Technology-related terms	Work-related terms
1. artificial intelligence	1. employment
2. computer vision	2. unemployment
3. speech recognition	3. unemployed
4. machine learning	4. labo(u)r
5. image recognition	5. labo(u)r market
6. intelligence system(s)	6. work(s)
7. deep learning	7. future of work(s)|job(s)|employment(s)|profession(s)
8. neural network(s)	8. emerging work(s)|job(s)|employment(s)|profession(s)
9. facial recognition	9. new work(s)|job(s)|employment(s)|profession(s)
10. virtual assistant(s)	10. (fourth|4th) industrial revolution
11. reinforcement learning	11. industry 4.0
12. natural language processing	12. skill(s)
13. face recognition	13. re(-)skill(s|ing|ment)
14. autonomous vehicle(s)	14. up(-)skill(s|ing|ment)
15. predictive analytic(s)	15. personnel training(s)
16. self-driving	16. workforce
17. data scientist(s)	17. worker(s)
18. data science	18. occupation(s)
19. text analytic(s)	19. job(s)
20. data analytic(s)	20. production
21. data mining	21. productivity
22. automat(e|ed|ic|ion)	22. econom(y|ies|ic)
23. digital	
24. robot(s)	
25. machine(s)	
26. technolog(y|ies|ical)	
27. innovation(s)	

Step 2: Calculated overall score based on abstract

Abstract	Score
Do industries shed jobs when they adopt new labor-saving technologies? Sometimes productivity-enhancing technology increases industry employment instead. In manufacturing, jobs grew along with productivity for a century or more; only later did productivity gains bring declining employment. What changed? Markets became saturated. While the literature on structural change provides reasons for the decline in the manufacturing share of employment, few papers can explain both the rise and subsequent fall. Using two centuries of data, a simple model of demand accurately explains the rise and fall of employment in the US textile, steel, and automotive industries. The model helps explain why the Industrial Revolution was highly disruptive despite low productivity growth and why information technologies appear to have positive effects on employment today. (From: Automation and Jobs: When Technology Boosts Employment. (Bessen, 2018).	**employment (2*3) +** **productivity (0.5 *3) +** **job(s) (2*1) +** **labor (2*1) +** **technolog (0.25*2)**

Step 3: Calculated overall score based on title (example)

Title	Score
How artificial intelligence affect the **labour** market in Poland	Score_so_far + **'labour' (2*2)**

Step 4: Classification codes (example)

Classification codes	Score
70.12.6 Labour and Income	Score_so_far + **4**

Step 5: Main headings (example)

Main heading	Score
Employment	Score_so_far + **4**

Step 6: Additional keywords from abstract (example)

Matched keywords	Score
[**labour, employment, work, artificial intelligence, technology, innovations**]	Score_so_far + **scores of all unique keywords**
['job', 'position', 'automated', 'skills']	Score_so_far + **0**
['automation', 'machines', 'workers']	Score_so_far + **0.5**

Step 7: Industry Relevance (example)

Classification codes	Score
821 Agricultural Equipment and Methods	Overall_score***0.25**

A.6 Data Extraction Form

1. Research Scope (Level of aggregation)

A. Industry-level
B. Firm-level
C. Country-level
D. Comparative (cross-country)
E. Global
F. Other
Details of research scope (free form)

2. Was Canada studied in this article?

Yes
No

3. Study Type

A. Literature Review
B. Review (other than A)
C. Case Study
D. Survey or Interview
E. Data/Statistical Analysis
F. Other (e.g., using equations to justify or propose a framework)
Details of Study Type (free form)

For case study or data/statistical analysis, please specify the level:

A. Industry
B. Firm
C. Country
D. Comparative (cross-country)
E. Other

4. Data Source

A. Official Data (Government Source)
B. Collected Data
C. No Data (e.g., reflection, opinion, theme)
D. Other
Details of Data Source (free form)

5. Time Span of Data

Ex. 2010–2015
Free form

6. Digital Technology

Concept 1: Digital Technlogies
A. AI (ML, DL, NLP, etc.)
B. Robotics
C. Big Data
D. IoT
E. Cloud Computing
F. Other
Details of Digital Technology (free form)

Type of Digital Technology Impact
A. Automation of tasks/roles
B. Digitization/Data science
C. Training/reskilling/digital literacy
D. Other
Specify the impact of digital technologies mentioned (free form)

7. Effect on Employment
A. Positive on industry (e.g., increase in jobs, opportunities)
B. Positive on employees
C. Negative on industry (e.g., unemployment, layoffs)
D. Negative on employees
E. Neutral
F. Not specified
G. Other
Provide details on magnitude if given (free form)
Skills and Talent Gap
A. Yes
B. No
C. Mentioned
Provide more details here (free form)

8. Intervention
Includes policy, training, regulation, etc.
A. Yes, quantitative
B. Yes, qualitative
C. No
D. Other
Provide details on the intervention (free form)

9. Forecast/Projection on Employment
Includes policy, training, regulation, etc.
A. Yes, quantitative
B. Yes, qualitative
C. No
D. Other
If yes, what is the forecast? (free form)

10. Forecast/Projection on Transformation
Innovation and adoption of digital technologies
A. Yes, quantitative
B. Yes, qualitative
C. No
D. Other
If yes, what is the forecast? (free form)

APPENDIX B: Search Terms for EV and WoS

Engineering Village
Date Retrieved: March 19, 2021

(((((learning (artificial intelligence) or cloud computing or artificial intelligence or data mining or big data or machine learning or predictive analytics or Internet of Things or data analysis or deep learning or neutral nets or feature extraction or neural networks or learning algorithms or support vector machines or automation or computer vision or remote sensing or robotics or data analytics or heuristic algorithms or intelligent computing or recommender systems or data science or clustering algorithms or data acquisition or advanced analytics or convolutional neural networks or mobile computing or intelligent systems or mobile robots or logistic regression or multilayer neural networks or virtual reality or deep neural networks or natural language processing systems or natural language processing or computational linguistics or speech recognition or text analysis or pattern classification or learning systems or text mining or text processing or sentiment analysis or speech processing or pattern clustering or speech synthesis or ontologies (artificial intelligence or recurrent neural nets or industrial robots or robots or robot applications or computer aided manufacturing or intelligent robots or robots, industrial or agricultural robots or medical robotics or service robots)) WN ALL)))

Web of Science
Date Retrieved: March 19, 2021

AB=(learning (artificial intelligence) OR cloud computing OR artificial intelligence OR data mining OR big data OR machine learning OR predictive analytics OR Internet of Things OR data analysis OR deep learning OR neutral nets OR feature extraction OR neural networks OR learning algorithms OR support vector machines OR automation OR computer vision OR remote sensing OR robotics OR data analytics OR heuristic algorithms OR intelligent computing OR recommender systems OR data science OR clustering algorithms OR data acquisition OR advanced analytics OR convolutional neural networks OR mobile computing OR intelligent systems OR mobile robots OR logistic regression OR multilayer neural networks OR virtual reality OR deep neural networks OR natural language processing systems OR natural language processing OR computational linguistics OR speech recognition OR text analysis OR pattern classification OR learning systems OR text mining OR text processing OR sentiment analysis OR speech processing OR pattern clustering OR speech synthesis OR ontologies (artificial intelligence OR recurrent neural nets OR industrial robots OR robots OR robot applications OR computer aided manufacturing OR intelligent robots OR robots, industrial OR agricultural robots OR medical robotics OR service robots))

APPENDIX C: Search terms for Keywords Everywhere, Google Trends

Note: each term was searched separately
tensorflow, pytorch, keras-python, theano, numpy, scipy, scikitlearn, pandas-python, and matplotlib

APPENDIX D: Factiva (Newspaper Data) Search Terms

("cloud computing" OR "artificial intelligence" OR "data mining" OR "big data" OR "machine learning" OR "predictive analytics" OR "Internet of Things" OR "data analysis" OR "deep learning" OR "neutral nets" OR "feature extraction" OR "neural networks" OR "learning algorithms" OR "support vector machines" OR "automation" OR "computer vision" OR "remote sensing" OR "data analytics" OR "heuristic algorithms" OR "intelligent computing" OR "recommender systems" OR "data science" OR "clustering algorithms" OR "data acquisition" OR "advanced analytics" OR "mobile computing" OR "intelligent systems" OR "logistic regression" OR "virtual reality" OR "natural language processing systems" OR "natural language processing" OR "computational linguistics" OR "speech recognition" OR "text analysis" OR "pattern classification" OR "learning systems" OR "text mining" OR "text processing" OR "sentiment analysis" OR "speech processing" OR "pattern clustering" OR "speech synthesis" OR "recurrent neural nets" OR robot* OR "computer aided manufacturing")

APPENDIX E: List of global consulting firms and Canadian think tanks analysed

Global Consulting Firms	**Canadian Think Tanks**
Accenture Canada	Asia Pacific Foundation
Accenture	AMII
Bain & Company	Atlantic Institute for Market Studies
Booz Allen Hamilton	Atlantic Provinces Economic Council
Boston Consulting Group (BCG) Canada	Brookfield Institute
Boston Consulting Group (BCG)	Business Council of Canada
Capgemini Canada	C.D. Howe Institute
Capgemini	Canada 2020
Deloitte Consulting Canada	Canada West Foundation
Deloitte Consulting	Canada's Public Policy Forum
Ernst & Young (EY) Canada	Canadian Centre for Policy Alternatives
Ernst & Young (EY)	Canadian Global Affairs Institute
EY-Parthenon	Canadian Institute of Advanced Research
Gartner	Canadian Foundation for the Americas
GE Healthcare Partners Canada	Canadian Urban Institute
GE Healthcare Partners	Cardus
Grant Thornton Canada	Centre for International Governance Innovation
Grant Thornton	Centre for the Study of Living Standards
IBM Canada	Conference Board of Canada
IBM	Council of Canadian Academies
Kearney Canada	Fraser Institute
Kearney	Frontier Centre for Public Policy
KPMG Canada	Future Skills Canada
KPMG	Institute for Citizen-Centred Service
L.E.K. Consulting	Institute for Research on Public Policy
Lockheed Martin Corportation Canada	Institute of Public Administration of Canada
Lockheed Martin Corportation	Institute on Governance
McKinsey & Company Canada	International Institute for Sustainable Development
McKinsey & Company	Macdonald-Laurier Institute
Mercer Canada	MILA
Mercer	Montreal Economic Institute
Navigant Consulting	Mowat Centre
North Grumman Corporation	Northern Policy Institute
Oliver Wyman	Parkland Institute
Oracle Canada	Pearson Centre for Progressive Policy
Oracle	Social Research and Demonstration Corporation
PricewaterhouseCoopers (PwC) Canada	Vector Institute
PricewaterhouseCoopers (PwC)	
SAP Serviecs Canada	
SAP Serviecs	
Strategy&	

APPENDIX F: Grouping of industries

Agriculture, forestry, fishing and hunting	11 Agriculture, forestry, fishing and hunting • crop production • animal production • aquaculture • forestry • logging • fishing • hunting and trapping • agricultur* • farming • groves • greenhouse • floriculture • nurser* • timber tract
Mining	21 Mining, quarrying, and oil and gas extraction • oil extraction • oils and extraction • oil sand extraction • gas extraction • mining industry • quarrying • mining firm* • mining compan*
Construction	23 Construction • building construction • heavy construction • civil engineering • Land subdivision • contractors construction • home builders
Manufacturing	31-33 Manufacturing • manufacture • manufacturing • milling • mills • meat processing • food processing • product preparation • product packaging • breweries • wineries • distilleries

Wholesale and retail trade	41 Wholesale trade • wholesale • wholesaler* • business-to-business market • business-to-business agent • business-to-business broker • distributors 44-45 Retail trade • retailers • retail trade • shopping malls • stores • gas* stations
Transportation, information and commu- nications and utilities	22 Utilities • power generation • power transmission • power distribution • natural gas distribution • water system* • sewage system* • hydro-electric • irrigation systems • sewage treatment* 56 waste management and remediation services • waste collection • waste treatment • waste disposal • environmental remediation • waste management) 48-49 Transportation and warehousing • transportation • trucking • railway* • railroads • transit • warehouse • warehousing • couriers • postal service 51 Information and cultural industries • publishing (industr*, firm* or compan*) • Motion picture (industr* firm* or compan*) • sound recording (industr, firm* or compan*) • broadcasting • telecommunications • telecom • data processing • data hosting • web hosting • news syndicates • libraries archive • web search portals

Finance, Insurance and real estate, rental and leasing	52 Finance, insurance • financial service* • Banking • Banks • monetary authority • central bank • credit intermediation • financial securities • commodity contracts • financial investment • insurance (industr*, firm*, compan*) • financial vehicles 53 Real estate, rental,leasing • real estate • rental • Lease • leasing
Services	54 Professional, scientific and technical services • legal (services, industry*, firm*, compan*) • accounting (services, industry*, firm*, compan*) • tax preparation • bookkeeping (services, industry*, firm*, compan*) • payroll (services, industry*, firm*, compan*) • architectural (services, industry*, firm*, compan*) • engineering (services, industry*, firm*, compan*) • Specialized design services • computer systems design (services, industry*, firm*, compan*) • management consulting • consulting (services, industry*, firm*, compan*) • scientific consulting • technical consulting • scientific research services • advertising (services, industry*, firm*, compan*) • public relations (services, industry*, firm*, compan*) • professional services 55 Management of companies and enterprises • management of companies • management of enterprise(s) • management of organization(s) • management of organisation(s) 56 Administrative and support • office administrative • facilities support • employment services • business support services • travel arrangement services • travel reservation services • Investigation services • security services • services to buildings • services to dwellings

	61 Educational services • colleges • cegeps • universities • computer training • management training • schools • educational support 62 Health care and social assistance • health care • healthcare • ambulatory • hospitals • nursing • residential care • elder care • old age homes • social assistance 71 Arts, entertainment and recreation • performing arts • spectator sports • heritage institutions • amusement industries • gambling industries • recreation industries • museums • historic sites • heritage sites • zoos • botanical gardens • nature parks • arts and entertainment 72 Accommodation and food services • travel accommodation • hotels • motels • cafeteria • recreational camps • rooming houses • boarding houses • food service* • drinking places • pubs • restaurants • eating places • take-out 81 Other services (except public administration) • repair and maintenance • personal services • laundry services • religious organizations • civic organizations • professional organizations • private households 91 Public administration • government offices • government service* • Public administration

APPENDIX G: Keywords used for NSERC and SSHRC databases

(Artificial Intelligence) or (Supervised Learning) or (Computer vision) or (Speech recognition) or (Machine learning) or (Unsupervised learning) or (Image recognition) or (Intelligence systems) or (Deep learning) or (Neural networks) or (Facial recognition) or (Virtual assistant) or (Reinforcement learning) or (Natural language processing) or (Face recognition) or (Autonomous vehicle) or (Predictive analytics) or (Robotics) or (Self-driving)

APPENDIX H: Official Data Sources

A list of data sources used from Statistics Canada, the US Bureau of Economic Analysis, and the US Bureau of Labor Statistics:

Amanda Sinclair. 2019. Measuring digital economic activities in Canada: Initial estimates, Statistics Canada. Available online at: https://www150.statcan.gc.ca/n1/en/pub/13-605-x/2019001/article/00002- eng.pdf, Last accessed 22 June 2021.

Statistics Canada. 2021. Table 27-10-0005-01 Federal expenditures on science and technology in current and constant dollars (x 1,000,000). Available online at: https://doi.org/10.25318/2710000501-eng, Last accessed 22 June 2021.

Statistics Canada. 2021. Table 27-10-0026-01 Federal expenditures on science and technology, by major departments and agencies - Intentions. Available online at: https://doi.org/10.25318/2710002601-eng, Last accessed 22 June 2021.

Statistics Canada. 2021. Table 27-10-0333-01 Business enterprise in-house research and development expenditures, by industry group based on the North American Industry Classification System (NAICS), country of control and expenditure types (x 1,000,000). Available online at: https://doi.org/10.25318/2710033301-eng, Last accessed 22 June 2021.

Statistics Canada. 2021. Table 36-10-0434-06 Gross domestic product (GDP) at basic prices, by industry, annual average, industry detail (x 1,000,000). Available online at: https://doi.org/10.25318/3610043401-eng, Last accessed 22 June 2021.

Statistics Canada. 2020. Industrial research and development characteristics, 2018 (actual), 2019 (preliminary) and 2020 (intentions), Available online at: https://www150.statcan.gc.ca/n1/daily-quotidien/201209/dq201209b-eng.htm Last Accessed 15 August 2021.

Statistics Canada. Table 14-10-0287- 01 Labour force characteristics, monthly, seasonally adjusted and trend-cycle, last 5 months. https://doi. org/10.25318/1410028701-eng

Statistics Canada. Table 36-10- 0104-01 Gross domestic product, expenditure-based, Canada, quarterly (x 1,000,000). https://doi. org/10.25318/3610010401-eng

U.S. Bureau of Labor Statistics, Civilian Labor Force Level [CLF16OV], retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/ CLF16OV

U.S. Bureau of Economic Analysis, Gross Private Domestic Investment: Fixed Investment: Nonresidential: Equipment [Y033RC1Q027SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/Y033RC1Q027SBEA

APPENDIX I. Final List of 319 Articles Resulting from the Systematic Literature Review

L1. Aamer, A., Eka Yani, L., & Alan Priyatna, Im. (2020). Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting. Operations and Supply Chain Management: An International Journal, 14(1), 1–13. https://doi.org/10.31387/oscm0440281

L2. Abeliansky, A. L., Algur, E., Bloom, D. E., & Prettner, K. (2020). The future of work: Meeting the global challenges of demographic change and automation. International Labour Review, 159(3), 285–306. https://doi.org/10.1111/ilr.12168

L3. Acemoglu, D., & Restrepo, P. (2017a). Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation (Working Paper No. 23077; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w23077

L4. Acemoglu, D., & Restrepo, P. (2017b). Robots and Jobs: Evidence from US Labor Markets (Working Paper No. 23285; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w23285

L5. Acemoglu, D., & Restrepo, P. (2018a). Artificial Intelligence, Automation and Work (Working Paper No. 24196; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w24196

L6. Acemoglu, D., & Restrepo, P. (2018b). Demographics and Automation (Working Paper No. 24421; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w24421

L7. Acemoglu, D., & Restrepo, P. (2018c). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review, 108(6), 1488–1542. https://doi.org/10.1257/aer.20160696

L8. Acemoglu, D., & Restrepo, P. (2019a). The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand (Working Paper No. 25682; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w25682

L9. Acemoglu, D., & Restrepo, P. (2019b). Automation and New Tasks: How Technology Displaces and Reinstates Labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

L10. Adams, A. (2018). Technology and the labour market: The assessment. Oxford Review of Economic Policy, 34(3), 349–361. https://doi.org/10.1093/oxrep/gry010

L11. Admiraal, W., Post, L., Guo, P., Saab, N., Makinen, S., Rainio, O., Vuori, J., Bourgeois, J., Kortuem, G., & Danford, G. (2019). Students as Future Workers: Cross-border Multidisciplinary Learning Labs in Higher Education. International Journal of Technology in Education and Science, 3(2), 85–94.

L12. Aghion, P., Jones, B. F., & Jones, C. I. (2017). Artificial Intelligence and Economic Growth (Working Paper No. 23928; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w23928

L13. Aguilera, A., & Ramos Barrera, M. G. (2016). Technological Unemployment: An approximation to the Latin American Case. AD-Minister, 29, 58–78. https://doi.org/10.17230/ad-minister.29.3

L14. Al-Htaybat, K., von Alberti-Alhtaybat, L., & Alhatabat, Z. (2018). Educating digital natives for the future: Accounting educators' evaluation of the accounting curriculum. Accounting Education, 27(4), 333–357. https://doi.org/10.1080/09639284.2018.1437758

L15. Alves, A. P. S. V. (2020). Achieving the Right to Work in the Face of Technological Advances: Reflections on the Occasion of the ILO's Centenary. University of Bologna Law Review, 5(1), 226–233. https://doi.org/10.6092/issn.2531-

6133/11393

L16. Armour, J., Parnham, R., & Sako, M. (2021). Unlocking the potential of AI for English law. International Journal of the Legal Profession, 28(1), 65–83. https://doi.org/10.1080/09695958.2020.1857765

L17. Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. Economics Letters, 159, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

L18. Arogyaswamy, B. (2020). Big tech and societal sustainability: An ethical framework. AI & Society, 35(4), 829–840. https://doi.org/10.1007/s00146-020-00956-6

L19. Assante, D., Romano, E., Flamini, M., Castro, M., Martin, S., Lavirotte, S., Rey, G., Leisenberg, M., Migliori, M. O., Bagdoniene, I., Gallo, R. T., Pascoal, A., & Spatafora, M. (2018). Internet of Things education: Labor market training needs and national policies. 2018 IEEE Global Engineering Education Conference (EDUCON), 1846–1853. https://doi.org/10.1109/EDUCON.2018.8363459

L20. Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives, 29(3), 3–30. https://doi.org/10.1257/jep.29.3.3

L21. Autor, D., & Salomons, A. (2018a). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share (Working Paper No. 24871; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w24871

L22. Autor, D., & Salomons, A. (2018b). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share (Working Paper No. 24871; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w24871

L23. Avdeeva, E. A., Averina, T. A., Davydova, T. E., & Zhutaeva, E. N. (2020). Automation of Russian industry as an indispensable condition for sustainable economic development in the digital environment. IOP Conference Series: Materials Science and Engineering, 862, 042041. https://doi.org/10.1088/1757-899X/862/4/042041

L24. Bahrin, M. A. K., Othman, M. F., Azli, N. H. N., & Talib, M. F. (2016). Industry 4.0: A Review on Industrial Automation and Robotic. Jurnal Teknologi, 78(6–13), Article 6–13. https://doi.org/10.11113/jt.v78.9285

L25. Ballestar, M. T., Díaz-Chao, Á., Sainz, J., & Torrent-Sellens, J. (2020). Knowledge, robots and productivity in SMEs: Explaining the second digital wave. Journal of Business Research, 108, 119–131. https://doi.org/10.1016/j.jbusres.2019.11.017

L26. Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. Research Policy, 48(8), 103765. https://doi.org/10.1016/j.respol.2019.03.010

L27. Barro, S., & Davenport, T. H. (2019, June 11). People and Machines: Partners in Innovation. MIT Sloan Management Review. https://sloanreview.mit.edu/article/people-and-machines-partners-in-innovation/

L28. Basso, G., Peri, G., & Rahman, A. S. (2020). Computerization and immigration: Theory and evidence from the United States. Canadian Journal of Economics/Revue Canadienne d'économique, 53(4), 1457–1494. https://doi.org/10.1111/caje.12472

L29. Basso, H. S., & Jimeno, J. F. (2021). From secular stagnation to robocalypse? Implications of demographic and technological changes. Journal of Monetary Economics, 117, 833–847. https://doi.org/10.1016/j.jmoneco.2020.06.004

L30. Bauer, W., Schlund, S., & Vocke, C. (2018). Working Life Within a Hybrid World – How Digital Transformation and Agile Structures Affect Human Functions and Increase Quality of Work and Business Performance. In J. I. Kantola, T. Barath, & S. Nazir (Eds.), Advances in Human Factors, Business Management and Leadership (pp. 3–10). Springer International Publishing. https://doi.org/10.1007/978-3-319-60372-8_1

L31. Bauer, W., & Vocke, C. (2020). Work in the Age of Artificial Intelligence – Challenges and Potentials for the Design of New Forms of Human-Machine Interaction. In J. I. Kantola & S. Nazir (Eds.), Advances in Human Factors, Business Management and Leadership (pp. 493–501). Springer International Publishing. https://doi.org/10.1007/978-3-030-20154-8_45

L32. Beer, P., & Mulder, R. H. (2020). The Effects of Technological Developments on Work and Their Implications for Continuous Vocational Education and Training: A Systematic Review. Frontiers in Psychology, 0. https://doi.org/10.3389/fpsyg.2020.00918

L33. Benmousa, N., Mansouri, K., Qbadou, M., & Illoussamen, E. (2018). The Impact Of Technological Evolution on the Labor Market and the Skills of Academics: Case "Adequacy Between University Training Offers and the Job Market." ICERI2018 Proceedings, 3154–3164.

L34. Bernstein, A., & Raman, A. (2015, June 1). The Great Decoupling: An Interview with Erik Brynjolfsson and Andrew McAfee. Harvard Business Review. https://hbr.org/2015/06/the-great-decoupling

L35. Bertani, F., Ponta, L., Raberto, M., Teglio, A., & Cincotti, S. (2019, May 30). An economy under the digital transformation [MPRA Paper]. https://mpra.ub.uni-muenchen.de/94205/

L36. Bertulfo, D. J., Gentile, E., & Vries, G. J. de. (2019). The Employment Effects of Technological Innovation, Consumption, and Participation in Global Value Chains: Evidence from Developing Asia (Bangladesh, China, People's Republic of, India, Indonesia, Korea, Republic of, Malaysia, Mongolia, Philippines, Singapore, Sri Lanka, Taipei,China, Viet Nam; Issue 572). Asian Development Bank. https://www.adb.org/publications/employment-technological-innovation-gvcs-asia

L37. Bessen, J. (2019). Automation and jobs: When technology boosts employment*. Economic Policy, 34(100), 589–626. https://doi.org/10.1093/epolic/eiaa001

L38. Bessen, J. E. (2016). How Computer Automation Affects Occupations: Technology, Jobs, and Skills (SSRN Scholarly Paper ID 2690435). Social Science Research Network. https://doi.org/10.2139/ssrn.2690435

L39. Bhattacharyya, S. S. S., & Nair, S. (2019). Explicating the future of work: Perspectives from India. Journal of Management Development, 38(3), 175–194. https://doi.org/10.1108/JMD-01-2019-0032

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L41. Bissessur, J., Arabikhan, F., & Bednar, P. (2020). The Illusion of Routine as an Indicator for Job Automation with Artificial Intelligence. In A. Lazazzara, F. Ricciardi, & S. Za (Eds.), Exploring Digital Ecosystems (pp. 407–416). Springer International Publishing. https://doi.org/10.1007/978-3-030-23665-6_29

L42. Bláha, J., Klimsza, L., Lokaj, A., & Nierostek, L. (2021). Multidimensional Analysis of Ethical Leadership for Business Development. European Journal of Sustainable Development, 10(1), 290–290. https://doi.org/10.14207/ejsd.2021.v10n1p290

L43. Blankemeyer, S., Recker, T., Stuke, T., Brokmann, J., Geese, M., Reiniger, M., Pischke, D., Oubari, A., & Raatz, A. (2018). A Method to Distinguish Potential Workplaces for Human-Robot Collaboration. Procedia CIRP, 76, 171–176. https://doi.org/10.1016/j.procir.2018.02.008

L44. Blit, J. (2020). Automation and Reallocation: Will COVID-19 Usher in the Future of Work? Canadian Public Policy, 46(S2), S192–S202. https://doi.org/10.3138/cpp.2020-065

L45. Bobade, D. (2018). Digitalization and women entrepreneurs. Sansmaran Research Journal Special Issue, 1–10.

L46. Bogoviz, A. V., Gulyaeva, T. I., Semenova, E. I., & Lobova, S. V. (2019). Transformation Changes in the System of Professional Competences of a Modern Specialists in the Conditions of Knowledge Economy's Formation and the Innovational Approach to Training. In E. G. Popkova, Y. V. Ragulina, & A. V. Bogoviz (Eds.), Industry 4.0: Industrial Revolution of the 21st Century (pp. 193–200). Springer International Publishing. https://doi.org/10.1007/978-3-319-94310-7_19

L47. Boyd, R., & Holton, R. J. (2018). Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? Journal of Sociology, 54(3), 331–345. https://doi.org/10.1177/1440783317726591

L48. Braña, F.-J. (2019). A fourth industrial revolution? Digital transformation, labor and work organization: a view from Spain. Journal of Industrial and Business Economics, 46(3), 415–430. https://doi.org/10.1007/s40812-019-00122-0

L49. Britton, B. L., & Atkinson, D. G. (2016). An Investigation into the Significant Impacts of Automation in Asset Management. Economic and Social Development: Book of Proceedings. https://www.proquest.com/openview/31fd969cbfdb9c40426be48d3566092a/1?pq-origsite=gscholar&cbl=2033472

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L51. Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics (Working Paper No. 24001; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w24001

L52. Byhovskaya, A. (2017). Robots versus workers: Towards an open, equitable and inclusive digital economy. Organisation for Economic Cooperation and Development. The OECD Observer. https://doi.org/10.1787/f96f9ce7-en

L53. Byrne, D. M., Fernald, J. G., & Reinsdorf, M. B. (2016). Does the United States Have a Productivity Slowdown or a Measurement Problem? Brookings Papers on Economic Activity, 109–157.

L54. Calitz, A. P., Poisat, P., & Cullen, M. (2017). The future African workplace: The use of collaborative robots in manufacturing. SA Journal of Human Resource Management, 15(0), 11. https://doi.org/10.4102/sajhrm.v15i0.901

L55. Camiña, E., Díaz-Chao, Á., & Torrent-Sellens, J. (2020). Automation technologies: Long-term effects for Spanish industrial firms. Technological Forecasting and Social Change, 151, 119828. https://doi.org/10.1016/j.techfore.2019.119828

L56. Carey, D. (2017). Adapting to the changing labour market in New Zealand. OECD Economics Department Working Papers. https://doi.org/10.1787/e6ced642-en

L57. Carnevale, A. P., Ridley, N., Cheah, B., Strohl, J., & Campbell, K. P. (2019). Upskilling and Downsizing in American Manufacturing. In Georgetown University Center on Education and the Workforce. Georgetown University Center on Education and the Workforce. https://eric.ed.gov/?id=ED600085

L58. Casalino, N., Borin, B., Pizzolo, G., & Cavallini, S. (2019). Automation, Technology Transfer and Managerial Practices for Organizational Growth of SMEs. A Smart Curriculum for Competitiveness. 2019 IEEE Global Engineering Education Conference (EDUCON), 1534–1541. https://doi.org/10.1109/EDUCON.2019.8725229

L59. Casalino, N., Saso, T., Borin, B., Massella, E., & Lancioni, F. (2020). Digital Competences for Civil Servants and Digital Ecosystems for More Effective Working Processes in Public Organizations. In R. Agrifoglio, R. Lamboglia, D. Mancini, & F. Ricciardi (Eds.), Digital Business Transformation (pp. 315–326). Springer International Publishing. https://doi.org/10.1007/978-3-030-47355-6_21

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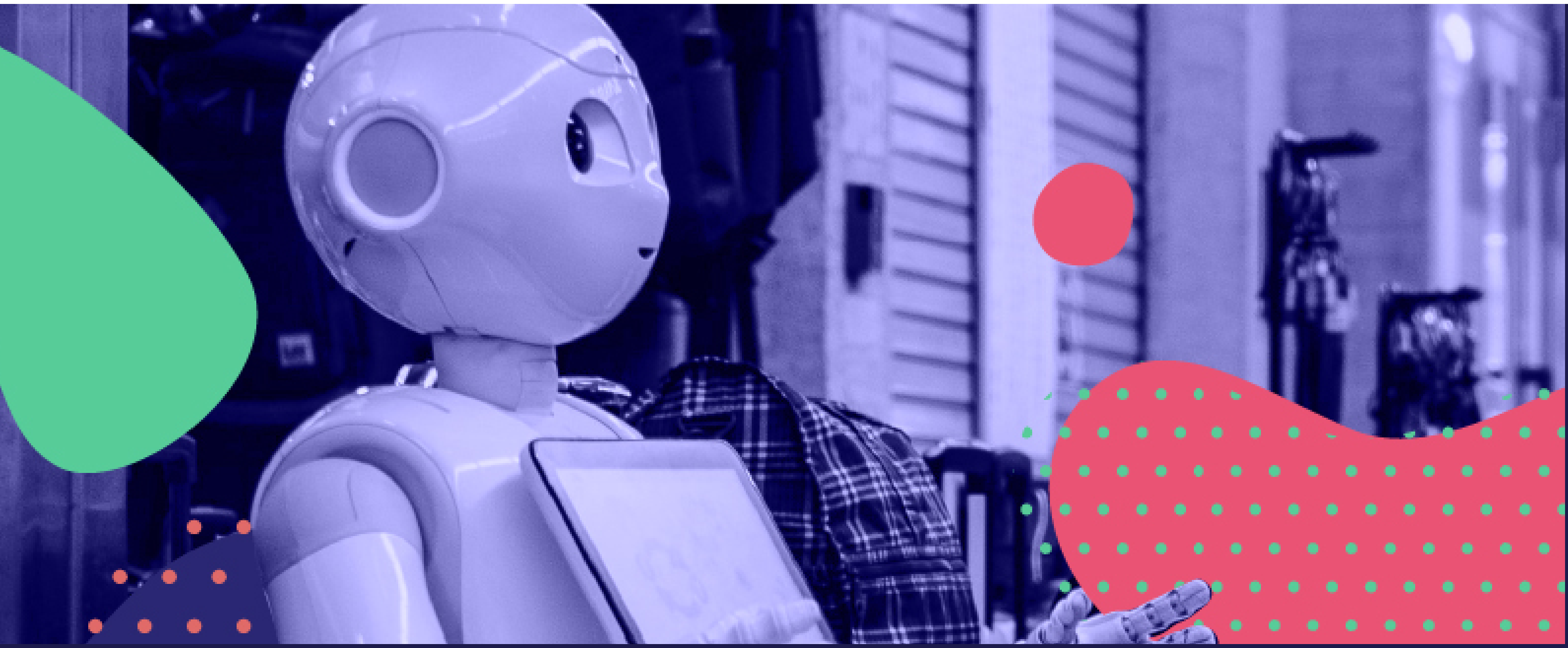
APPENDIX J: The Pace of Robotics Technology Adoption in Canada

The Pace of Robotics Technology Adoption in Canada: Covid-19 will likely slow the pace of robotics adoption in Canada, Future Jobs Canada Mini Report, Available from: https://futurejobscanada.economics.utoronto.ca/the-pace-of-robotics-technology-adoption-in-canada/



Future Jobs Canada

The Pace of Robotics Technology Adoption in Canada

Covid-19 will likely slow the pace of robotics adoption in Canada

Future Jobs Canada

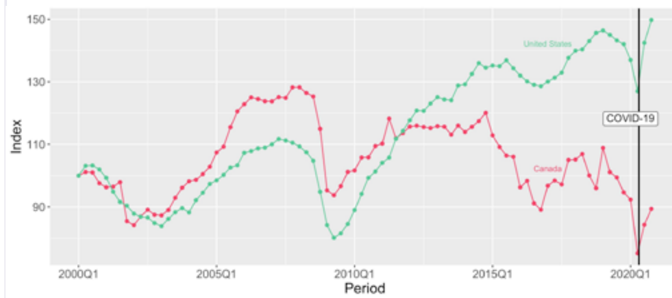
Canadian Investment in Machinery and Equipment Lags Behind the US

It is well known that investment in machinery and equipment per labour force participant in Canada has lagged behind that of the United States before the COVID-19 pandemic. This trend has continued through the early stages of the COVID-19 pandemic, during which both countries' investment patterns were severely affected by business closures and economic downturns. While the normalized investment data demonstrates that the US business investment patterns in machinery and equipment have returned to their pre-pandemic levels, Canada's remain significantly below (Figure 1).

Figure 1

Business Investment in Machinery and Equipment per Available Labour

Quarterly Data 2000 Q1 = 100



Date Source – Statistics Canada Bureau of Economic Analysis. Perios Observed 2000 Q1–2020 Q4

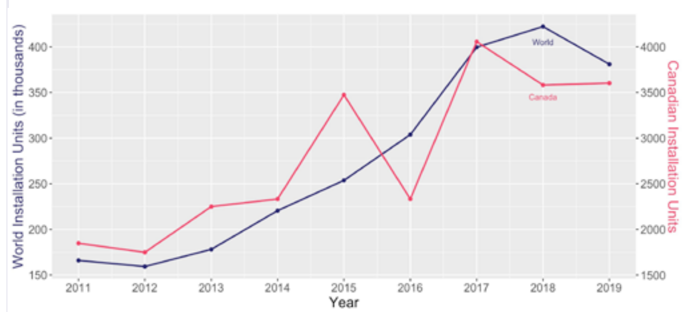
Canada Follows the Global Trend in Robotics Installations Pre-COVID-19

Data from the International Federation of Robotics World Robotics Reports indicate increased adoption of industrial robotics technology in the pre-pandemic period. Canada's data suggests that our companies have installed industrial robots at a similar pace, but this adoption has slowed in recent years (Figure 2). Between 2011 and 2019, Canada's installations grew by an average of 10.6% annually. During the same period, the world installations grew 14.4% annually on average.

Figure 2

World and Canadian Industrial Robots Installation

Annual Data



Date Source – International federation of Robotics. Period Observed: 2011 – 2019

The Pace of Global Industrial Automation is Forecasted to be Slowed by COVID-19

Economies worldwide continue to struggle with the impact of the pandemic. An examination of changes in the published robotics installations forecasts from the International Federation of Robotics (IFR) gives insights into the disruption and economic damage expected to be caused by COVID-19. Compared with the robotics forecasts from previous years, the 2020 forecasts show that the IFR expects the pandemic to slow global robot installations. Given the ongoing uncertainty surrounding the pace of economic recovery, the IFR has presented multiple projections of industrial robot installations over the next 3 years. All cases predict growth to be depressed in the short term (Figure 3). The expected impact of the pandemic on professional service robots is more muted. According to the report, professional service robots are projected to grow 38% in 2020 as the increased demand for medical service and industrial cleaning robots help offset decreased demand in other areas. While this is below the 41% growth they projected for 2020 the year prior, it is still up from the 32% growth for 2019 (Figure 4). The forecasted installation levels for personal service robot installations have also diminished as a result of the pandemic (Figure 5).

Figure 3

World Projected Installations of Industrial Robots

Annual Data. 2005 = 100

Dots represent observed values. Dashed lines represent forecast values.
Data Source: International Federation of Robotics. Period observed 2005–2023

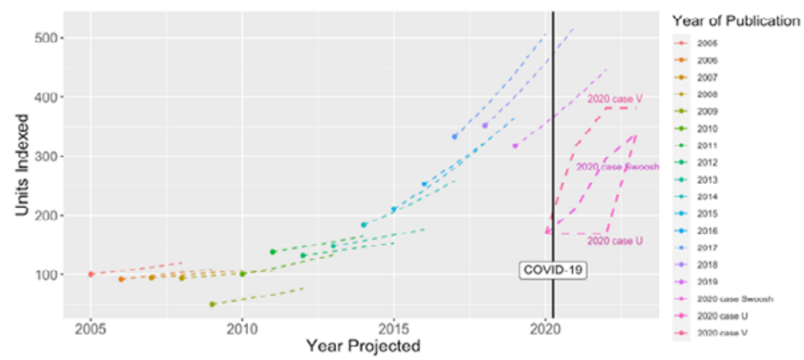


Figure 4

World Projected Installations of Professional Service Robots

Annual Data. 2005 = 100

Dots represent observed values. Dashed lines represent forecast values.
Data Source: International Federation of Robotics. Period observed 2005–2023

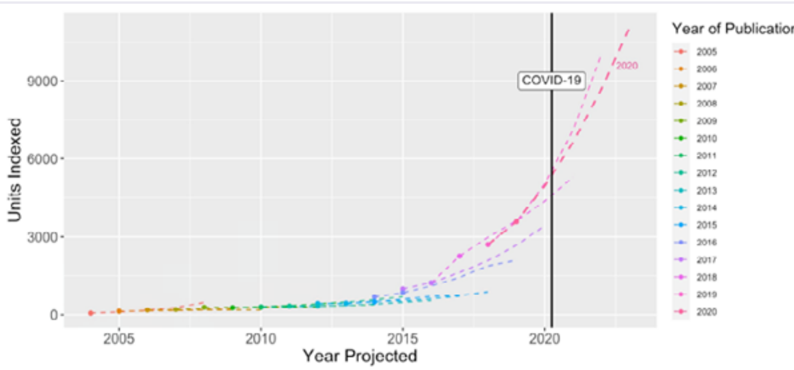
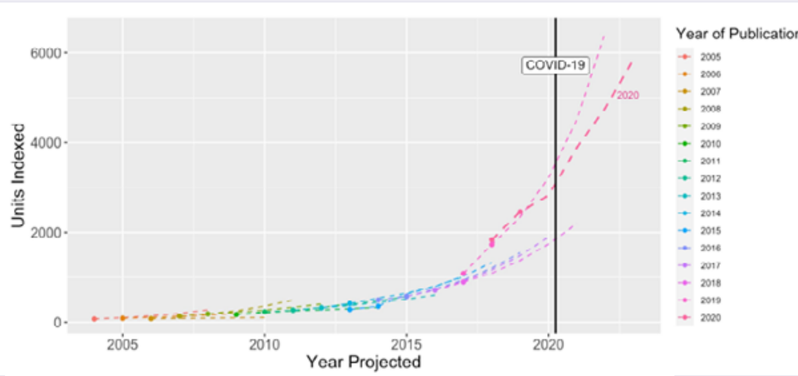


Figure 5

World Projected Installations of Personal Service Robots

Annual Data. 2005 = 100

Dots represent observed values. Dashed lines represent forecast values.
Data Source: International Federation of Robotics. Period observed 2005–2023



Global projection key takeaways:

- The COVID-19 pandemic is expected to reduce the pace of robotics adoption to varying degrees depending on the type of robots and their application.
- The expected pace of industrial automation highly depends on the pace of broad economic recovery.
- The COVID-19 pandemic is expected to reduce the potential level of industrial robot installations through 2023.
- A comparison of the IFR forecasts indicates that the growth of service robot adoption may be less affected by the pandemic than that of industrial robots.
- Based on historical similarities between global and Canadian robotic adoption rates alongside recent data on diminished investment in machinery and equipment in Canada during the pandemic, it is likely that the rate of robotics adoption in Canada will be dampened in the short run by the COVID-19 pandemic.
- If slower adoption rates materialize, the short-run disruptions in the labour market linked to increased adoption of robotics technologies may be attenuated.

Robotics definitions:

- Personal service robots include household task and entertainment robots such as vacuuming and floor cleaning robots, lawn-mowing robots, pool-cleaning robots, and toy robots.
- Professional service robots include robots used for commercial purposes. They are typically operated by trained professionals. Examples of this type include medical, farming, and professional cleaning robots.
- Industrial service robots refer strictly to those used for industrial automation applications.

Sources:

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- Installations of Industrial Robots, International Federation of Robotics World Robotics Industrial Robots Reports (Various Years)

Team

Researchers

Prof. Lyons is an Associate Professor in the Faculty of Information who is cross-appointed to the Dept. of Computer Science, an IBM Toronto Lab CAS Faculty Fellow, and a Faculty Affiliate of the Schwartz Reisman Institute for Technology and Society. She has authored numerous articles on knowledge mobilization in industrial settings based on NSERC-funded collaborative research and industry partnerships, and has recently organized several workshops devoted to exploring the future impacts of AI and data science on industry, diversity, and privacy issues. She is currently co-leading (with Prof. Alexopoulos) a research project funded by UCL And University of Toronto on COVID 19 Challenges, Economic, Individual, and Societal Impacts of Pandemic Responses on Cities with E. Lomas and A. Walford (UCL). She was the scientific lead in the development of a 2018 Networks of Centres of Excellence application (the Advanced Data Science Alliance – ADA) that brought together 124 researchers in 28 disciplines from 27 academic institutions, to engage with 51 industry partners and government policy makers with the goal of creating a multi-sectoral and trans-disciplinary national research network.

Prof. Alexopoulos, who was an academic co-leader of the ADA NCE's Employment, Economy, Policy, Diversity, and Training research theme, is a Professor of Economics who is cross appointed to the Faculty of Information. She is a Fellow of the Bank of Canada, a Canadian Productivity Partnership collaborator, and a Faculty Affiliate of the Schwartz Reisman Institute for Technology and Society and the School of Cities. She is a macroeconomist who has authored a number of papers on business cycles, technical change, economic uncertainty, labor markets and productivity and is a qualified legal expert in the fields of technical change, applied econometrics and macroeconomics. Her recent research focuses on creating measures of technical change based on text analysis of publications and patterns of library acquisitions. Her research, supported by a number of public and private grants, has been presented at numerous central banks, international conferences, academic departments, and the National Academy of Sciences. Profs Lyons and Alexopoulos have the breadth of cross-disciplinary knowledge and expertise needed to comment on and review the issues for this project. They will jointly address all parts of the project and will oversee and train research assistants to aid in the collection and analysis of the literature and data.

Research Assistants

Amanda Yang is pursuing a Masters of Information degree in Critical Information Policy Studies through the Faculty of Information from the University of Toronto. She has obtained a bachelor's degree in Justice, Political Philosophy & Law from McMaster University. Amanda works at the Gerstein Science Information Centre to support the instruction, research, and capacity-building for systematic and scoping review services, serving researchers, students, librarians, and faculty staff in the University of Toronto community. She is also involved in developing a living COVID-19 Information Guide with a Gerstein librarian team providing emerging research and resources for healthcare professionals, researchers, and the general public.

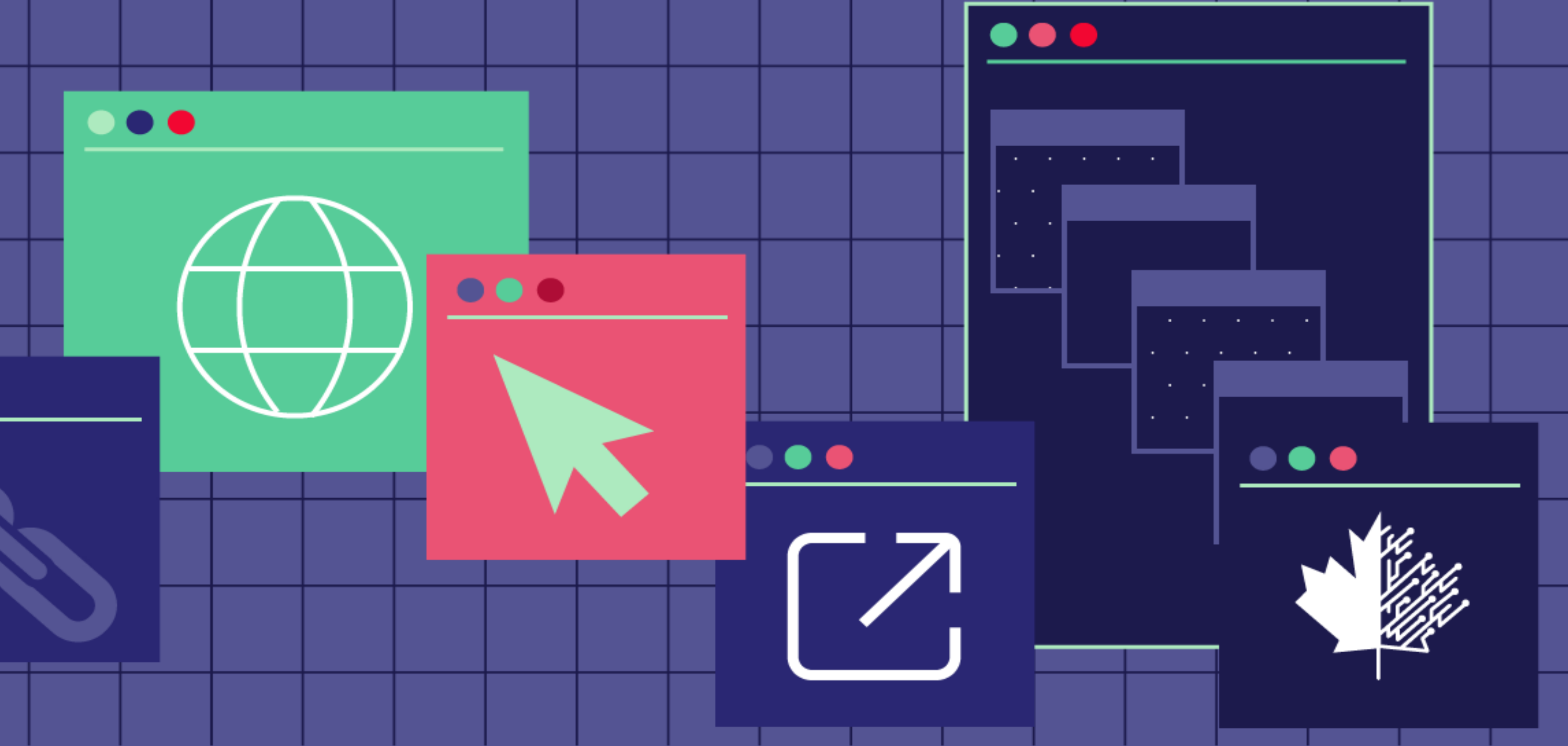
Hetav Pandya is pursuing a Bachelors of Computer Engineering with AI Minor through the faculty of Applied Science and Engineering at the University of Toronto. He serves as the Vice President – Academics at the University of Toronto Machine Intelligence Student Team (UTMIST) where he is responsible for planning and execution for academics events, supervising the progress of academic projects and organizing the annual MIST Conference.

Kaushar Mahetaji is a Master of Information candidate at the University of Toronto, focusing on Critical Information Policy Studies. Prior to joining the Faculty of Information , she completed her BSc in the Honours Integrated Science program at McMaster University, concentrating in biochemistry. Currently, Kaushar is an intern at the Gerstein Science Information Centre, where she supports the assessment, maintenance, and development of health science print and electronic collections and resources. She also assists with the creation of teaching material for knowledge syntheses workshops and the design and documentation of comprehensive search strategies.

Keli Chiu is a graduate student in Information at the University of Toronto with the concentration in Human-Centred Data Science. Before enrolling in iSchool, she worked as a web developer in startup companies where she had gained strong technical and collaboration skills. She had grown a tremendous interest in data science and analytics over the years and that passion led her to pursuit a Master in Information. Her research interests are natural language processing applications, text analysis and ethics in AI and machine learning.

Marcia Diaz-Agudelo is a multidisciplinary designer and is also a first year Information student at the University of Toronto. She obtained a Bachelor's degree in Design from Universidad de los Andes in Colombia. Marcia works as a staff designer at Open Privacy Research Society and has worked as a designer on projects in the intersection of design, technology and social justice such as the Digital Justice Lab. Marcia also works as an illustrator and has exhibited her work in Toronto and Mexico City.

Priscilla Layarda is a third-year economics specialist at the University of Toronto and a recipient of the full-ride Lester B. Pearson scholarship. She won the 2020 University of Toronto Excellence Award in the Natural Sciences and Engineering (UTEA-NSE) research grant to study complex problem-solving in teams with the Bernhard-Walther Lab. Previously, Priscilla was a lead analyst at the G7 Research Group, leading a global network of scholars in assembling, verifying, and disseminating information and analyses on G7 members' compliance with their summit commitment to reduce global digital inequality. Priscilla is an active pro-bono strategy consultant at 180 Degree Consulting and is currently chairing the Debates & Dialogue Committee at Hart House, hosting esteemed keynotes and panel discussions with experts, frontline workers, and policy-makers on socioeconomic issues.



Future Jobs Canada

Futurejobscanada@utoronto.ca

futurejobscanada.economics.utoronto.ca

@futurejobscan

UNIVERSITY OF TORONTO FACULTY OF INFORMATION

Economics UNIVERSITY OF TORONTO

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