Race Alongside the Machines

OCCUPATIONAL DIGITALIZATION TRENDS IN CANADA, 2006–2021

brookfield institute for innovation + entrepreneurship

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Future Skills Centre

Canada

The Future Skills Centre—Centre des Compétences futures (FSC-CCF) is a forward-thinking centre for research and collaboration dedicated to preparing Canadians for employment success. We believe Canadians should feel confident about the skills they have to succeed in a changing workforce. As a pan-Canadian community, we are collaborating to rigorously identify, test, measure, and share innovative approaches to assessing and developing the skills Canadians need to thrive in the days and years ahead.

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Foreword from the Future Skills Centre

THE PREVALENCE OF new digital tools and technologies in our daily lives is changing how we work and learn. The very nature of work in many jobs is transforming with more human activities being performed by or with the assistance of digital technology. As a result, we are seeing a greater demand for people and talent who can operate in an increasingly digital economy. Even before the pandemic, finding workers with the right skills to keep up with technological advancements in the workplace was a top of mind concern for Canadian employers.

In *Race Alongside the Machines*, authors Ibrahim Abduallail and Viet Vu chronicle the digitization of work over the last 15 years by examining the rise of digital skills through job classification frameworks, primarily by using the National Occupational Classification (NOC) and its American equivalent, O*NET. Their analysis confirms what many of us have already experienced one way or another—jobs that involve more repetitive or routine tasks saw the highest gains in digital advancements and integrations. However, the volume of these same jobs that experienced high digitization usually reached a plateau over time. This report also investigates how even non-repetitive jobs are increasingly demanding digital knowledge and skills, indicating that the most sought-after skills are constantly changing over time.

The Future Skills Centre is focused on helping everyone in Canada gain the skills they need to thrive in a changing labour market. Being able to make sense of the changing nature of skills and anticipate emerging labour demands is a key piece in preparing workers for the digitization of the future of work. Inequitable access to these technologies, infrastructure or training for in-demand digital skills can leave people behind. As we reflect on the report's findings, understanding that the degree of digitization and its impacts can and will be felt unevenly by different workers, we are committed to advancing knowledge that helps shape leading practices to ensure that everyone, especially underserved groups, can access career opportunities and participate in our shared prosperity.

Tricia Williams, PhD
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Executive Summary

MACHINES ARE HERE to stay, and there's no turning back. But technology doesn't have to be a force that "happens" to us. When implemented in a way that centres workers and their efforts, coupled with skills training investment, technology and automation can augment and complement workers, not replace them.

Jobs that once required little to no digital skills are increasingly requiring workers to adopt them into their day-to-day work tasks. Production outputs, resource needs and labour patterns are perpetually changing, and these changes require new thinking on how we prepare Canadians for the future of work.

This report offers a comprehensive look into how technology has impacted jobs and workers in the last 15 years. This information is designed to serve as a tool to understand the projected impact of technology on worker outcomes in Canada to ensure that we get the best and avoid the worst of technology-driven innovation.

In our 2019 report, *Who Are Canada's Tech Workers*, we developed an analytical framework to define technology workers. Now, we combine that framework with the National Occupational Classification (NOC). We use these to measure digital intensity and the rate of change in digital intensity across all occupations in Canada in the past 15 years, from 2006 to 2021. As the NOC lacks detailed data on the skills needed to perform each job, we use a crosswalk with the American equivalent, O*NETOnLine.

The results show that technology adoption has touched every single occupation in Canada—but differently. Our data supports global evidence that over the past 15 years, jobs requiring more routine tasks have overwhelmingly advanced in digital adoption as routine tasks were replaced with technology. But cloud computing, artificial intelligence, the Internet of Things (IoT), and big data are among the growing innovations in digital technology that are shifting the influence of digitalization to occupations that had previously been overwhelmingly non-routine.

We measure digital intensity and the rate of change in digital intensity across all occupations in Canada in the past 15 years, from 2006 to 2021.

Top six takeaways

1. **In the last 15 years, occupations associated with routine work saw the highest rates of digitalization.**
   Jobs with the highest rates of digitalization were those that managed data, i.e., property managers, health information management, railway conductors, and scheduling coordinators.

2. **In the last five years, however, jobs most associated with non-routine work are the top movers in digitalization.**
   The top occupations identified were photographic and film processors, physicians, and engineering inspectors.

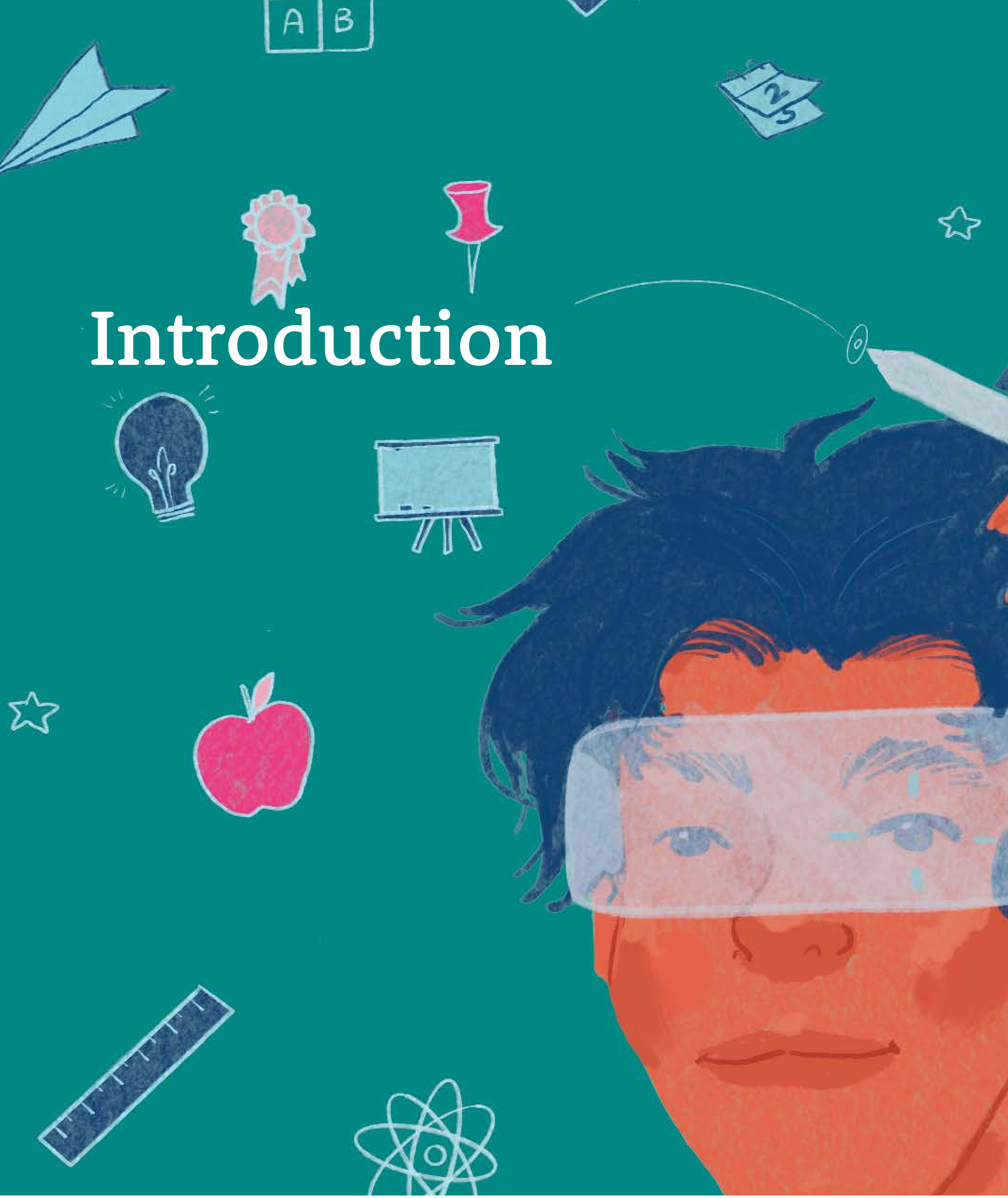
3. **Digital technologies assist workers with carrying out work requiring a high level of reasoning and analytical skills.**
   Workers who used technology to perform routine tasks saw more independence and autonomy in how they carried out their work, leaving them to focus on tasks that required more analytical thinking and higher reasoning.

4. **The fishing and agriculture sectors stand out as laggards in digital adoption.**
   Fishing and agricultural sector occupations had the lowest rates of digitalization, likely due to a wave of technological advancement that already happened in the 1990s, followed by stagnated progress since then. These sectors will need to adopt IoT and Cyber-Physical Systems (CPS) to prevent illegal, unreported, and unregulated fishing and become more sustainable.

5. **Pilots and translators were leading occupations for digital adoption between 2006 to 2016.**
   During the 2016 to 2021 period, however, their *pace of digitalization fell so significantly* that compared to other occupations across the total (15 year) period examined, they present as digital adoption laggards.

6. **Digital skills in highest demand are constantly changing over the years, which has implications for worker training and risks of hyper-specialization.**
   Malleability, critical thinking, and general knowledge across skills are vital to ensuring workers can adapt to the jobs of tomorrow.

Introduction



OVER THE PAST few decades, technology has completely transformed and reshaped the way many jobs are done. Both the skills needed and the tasks being completed by workers across different industries have undergone significant changes. As reliance on data and digital technology has increased, many jobs that once required little to no digital skills have become dependent on the abilities of workers to deal with databases and computer technology. For example, in healthcare professions, doctors, nurses, and other healthcare professionals now rely almost entirely on computer systems to log case details, follow up with patients, and communicate with other healthcare professionals working on the same case. Moloney and Farley (2015) explain that the healthcare professionals of today and tomorrow need to be experts in digital technology.

Such shifts that incorporate Information and Communication Technologies (ICTs) in the economy, and the associated need for workers to acquire digital literacy, has been one of the defining characteristics of the twenty-first century (Van Laar et. al. 2017). Many studies, including Bawden (2008) place emphasis on computer literacy as being one of the hallmarks of worker skills that will be in demand for the twenty-first century. Technological change is expected to continue to influence jobs and the demand for digital skills, and will continue to do so significantly in the future, with the adoption of cloud computing and the growth of e-commerce and big data (WEF 2020). Understanding which jobs have changed the most, and which type of digital skills are changing, is important in informing better policies to prepare workers for the future.

We found digitalization of work between 2006 and 2016 was most prevalent in occupations with high levels of routine tasks, or tasks that can be done by following a set of defined instructions, such as managing databases. In contrast, the changes in digitalization between 2016 and 2021 were much more focused on occupations with higher levels of non-routine tasks that require creative problem solving, such as engineering and medical professions. We discuss a phenomenon where certain jobs seem to experience significant changes in digitalization, followed by a period of plateau.

Understanding which jobs have changed the most, and which type of digital skills are changing, is important in informing better policies to prepare workers for the future.

Despite all occupations experiencing changes in digitalization, we find that three skills that make up the most technological occupations have remained unchanged in the 15-year period. We identified these as occupations with high intensity in three skills and knowledge areas: engineering design, programming, and engineering and technology. Finally, we show that the digital skills in highest demand are constantly changing over the years, which has implications for worker training and the risks of hyper-specialization.

Methodology

GIVEN THE DIVERSITY of work that people in Canada engage in, we need a structured way to group and organize occupations that are broadly similar together for our analysis. In Canada, the National Occupational Classification (NOC) provides a valuable classification of jobs, including within different skill groups. The most detailed level (which we use) distinguishes between detailed occupations, such as between a Computer Programmer and a Computer Engineer. In this study, we examine how important digital skills are across NOC occupations, observing patterns of change in digitalization across jobs from 2006 to 2021. As NOC lacks detailed data on the skills needed to perform these jobs, we use a crosswalk with the American equivalent, O*NETOnLine. Specifically, we connect O*NET v13 to NOC 2006, O*NET v21 to NOC 2016, and O*NET v26 to NOC 2021. In addition, as NOC goes through a major revision every ten years (with the last revision occurring in 2021), we aligned our classification to the 2011 version of NOC. This ensures that we're comparing against the same sets of occupations in our research.

Consistent with the approach to define technology workers established in Vu, Zafar, Lamb (2019), we focus on six specific skills, knowledge, and work activities related to digital literacy: Interacting with Computers, Computers and Electronics, Engineering Design, Engineering and Technology, Programming, and Telecommunications. Using these factors, we calculate the harmonic mean[1] of the scores in these six categories to produce the ranking system for digitalization in jobs for each of the three years. What we end up with through this process is a measure that is attached to each occupation that shows their relative digital intensity. For interpretability, we then transform this to a percentile measure.

We also look at the scores for each digital skill across each occupation individually, and normalize them using min-max feature scaling[2], to a scale of 0-1. Similar in ideas to converting the digital intensity score to percentiles, this makes the scores easier to interpret, with scores closer to 0 signalling lower digital skills, compared to scores closer to 1. We then analyze movements in both overall harmonized ranking and the normalized specific scores across the six different digital skills for each job, and across these three years.

Relative versus absolute measures

When comparing the rate of digitalization that different occupations experience, we focus not on absolute changes (that is, definitely saying one occupation is using more or less technology), but on relative changes (whether an occupation is seeing faster or slower rate of digitalization compared to other occupations).

In an ideal scenario, we would have focused on comparing absolute changes in digitalization that occupations experience, as that provides for a simpler interpretation. However, due to challenges associated with how O*NET's occupational attributes are constructed, this is not possible.

Since 2006, O*NET has gone through a gradual transition, from relying less on job incumbent surveys to generate data on occupational attributes, to increasingly relying on trained analysts in rating occupational attributes. The audit (Tsacoumis, Van Iddekinge 2006) that was conducted to evaluate the impact of this shift showed that while the implied ranking between occupations that were generated by incumbents and analysts matched well, incumbents tended to rate an occupational attribute to be more important (in magnitude) than analysts. That is, while the relative measure is preserved, there was a systematic downward shift in rating scores by moving to analyst ratings. Any standardization or normalization of scores across the years would have implicitly incorporated relative aspects into the occupational measures, and absolute changes that we can observe will also have been contaminated by it.

As a result, we made a conscious decision to focus entirely on constructing a relative measure (which was unaffected by the transition), that ensures it can be cleanly interpreted.

Workers, Augmented

WE FIRST LOOK at occupations with the fastest pace of digitalization between 2006 and 2021. Table 1 shows that among this group, two are healthcare-related professions (e.g. Health Information Management Occupations). Property administrators moved up most in the ranking, from being one of the least digitized occupations in 2006 (at 13th percentile) to the top quartile in 2021 (at 77th percentile).

Table 1

Top 10 movers from 2006 to 2021 (increased ranking in digital skills)

NOC title	Percentile in 2006	Percentile in 2016	Percentile in 2021
Property administrators	**13th**	59th	**77th**
Health information management occupations	**32nd**	47th	**89th**
Facility operation and maintenance managers	**13th**	59th	**69th**
Health policy researchers, consultants, and program officers	**27th**	87th	**84th**
Other sales related occupations	**8th**	31st	**58th**
Supervisors, supply-chain tracking, and scheduling co-ordination occupations	**25th**	80th	**77th**
Accommodation service managers	**36th**	82nd	**87th**
Painters, sculptors, and other visual artists	**34th**	69th	**85th**
Railway traffic controllers and marine traffic regulators	**12th**	56th	**56th**
Railway conductors and brakemen/women	**12th**	56th	**56th**

What these occupations (with a few exceptions, including painters, sculptors, and other visual artists) have in common, is the preponderance of routine tasks that comprise their work context. Routine tasks are job tasks for which one can write down an easy-to-follow set of instructions that anyone can repeat without much training. Autor and Dorn (2013) provide several examples to illustrate this, and explain that the specialization of the labour force in routine tasks had started in the 1980s. In an effort to study how computer technology affects job skills demand, Autor, Levy, and Murnane (2003) use a matrix to classify tasks and skills in the forms of routine versus non-routine, and cognitive versus manual. Almeida et. al. (2017) use this classification and identify work activities and work contexts from the O*NET database that can be linked to these four categories.

Table 3 details, for select occupations in the top ten list, tasks that are routine in nature. From this, we can infer that most of the digitalization occurring could be in the introduction of database-related technologies, and most of the digital improvement can likely be linked with the logistics side of the work.

When we use the framework identified in Table 2 to further understand the changes that workers in these top ten occupations experienced, we note that these occupations had a consistently higher score in O*NET work contexts that were routine in nature. While the average score across all occupations was around 65 (out of 100) for the "Importance of Repeating the Same Task" job context, for seven of the top ten occupations, the same score was higher. Another signal that suggests the impact of digital technology on these occupations' work context, is the score associated with the "pace determined by the speed of equipment" attribute. All ten occupations on the list saw a lower score in this work context in 2021 compared to 2006, denoting the increased speed with which computers operate, reducing speed of equipment as a barrier in production.

Table 2

Almeida et. al. (2017) classification of Work Context

	Manual	Cognitive
Routine	Pace determined by speed of equipment Spend time making repetitive motions Controlling machines and processes	Importance of being exact or accurate Importance of repeating same tasks Structured versus unstructured work
Non-routine	Spatial orientation Manual dexterity Operating vehicles, mechanized devices or equipment Spend time using your hands to handle, control, or feel objects, tools or controls	Analyzing data or information Thinking creatively Interpreting the meaning of information for others Coaching and developing others Guiding, directing, and motivating subordinates Establishing and maintaining interpersonal relationships

Perhaps most suggestively, an examination of the "structured versus unstructured" work context, where a higher score is associated with more freedom for workers in these occupations to determine their tasks and priorities, shows that occupational freedom increased significantly for all ten top movers over the sample period. This is consistent with the view that the removal of routine tasks leaves workers with higher shares of non-routine tasks, for which each individual worker is afforded more agency in making decisions on how to tackle such tasks. Cascio and Montealegre (2016) highlight the shifts in entire firm, work, and organizational structures due to technology, discussing the disruption that change tends to cause to all of these structures.

The removal of routine tasks leaves workers with higher shares of non-routine tasks, for which each individual worker is afforded more agency in making decisions on how to tackle such tasks.

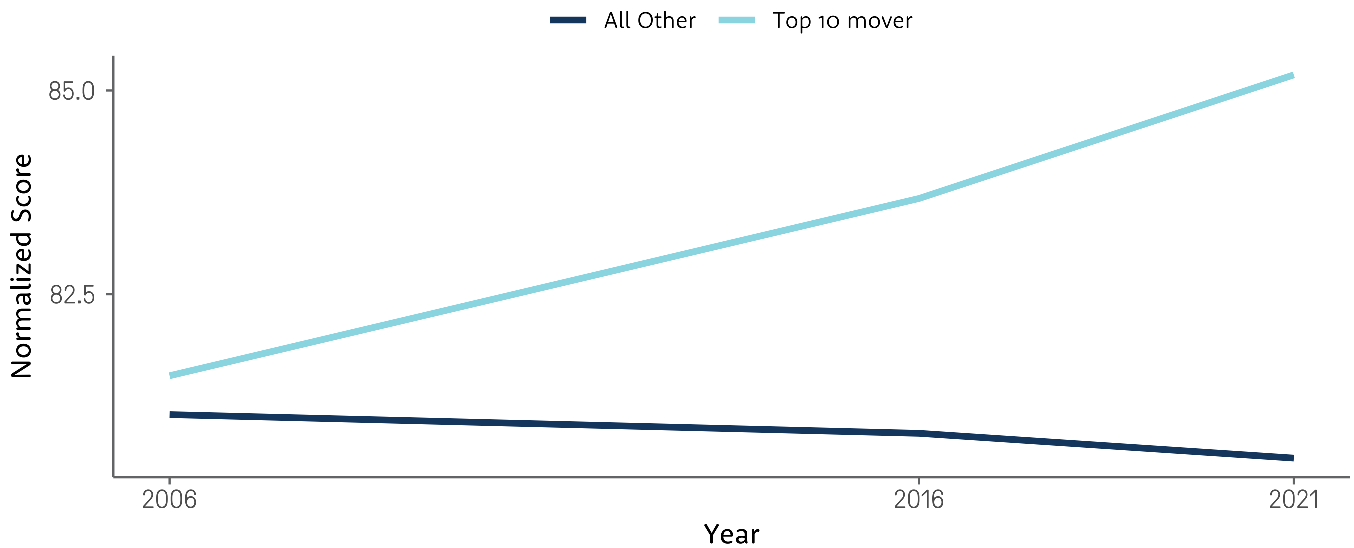
Table 3

Examples of tasks for NOC occupations

NOC occupation	Example tasks
Property administrators	• Compile and maintain records on operating expenses and income, prepare reports and review rents to ensure they are at market value • Prepare and administer contracts for provision of property services, such as cleaning and maintenance, security services, and alarm systems
Railway conductors and brakemen/women	• Communicate with train crew members by radio, signals, or by other means to give and receive train operation information • Collect fares on board passenger trains, announce approaching train stops, and answer passenger enquiries
Health information management occupations	• Collect, code, cross-reference, and store health records and related information • Operate information systems to maintain indexes for classification systems and to manage and retrieve health records information

Figure 1

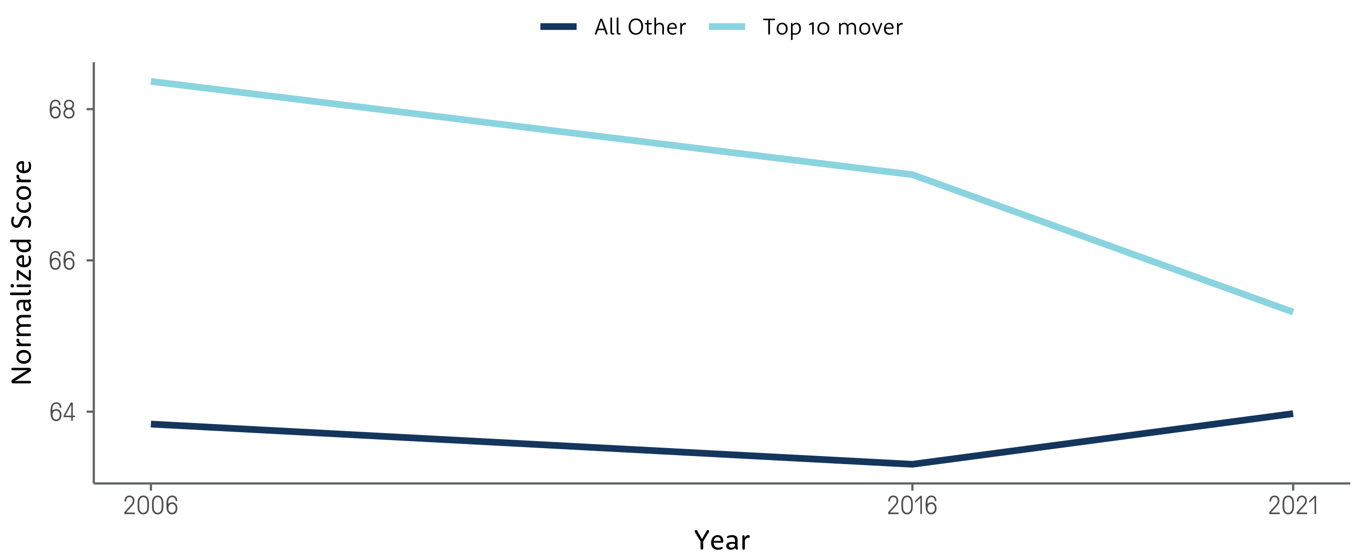
Work context—structured vs unstructured—Canadian occupations 2006-2021



Source: O*Net, Author Calculations

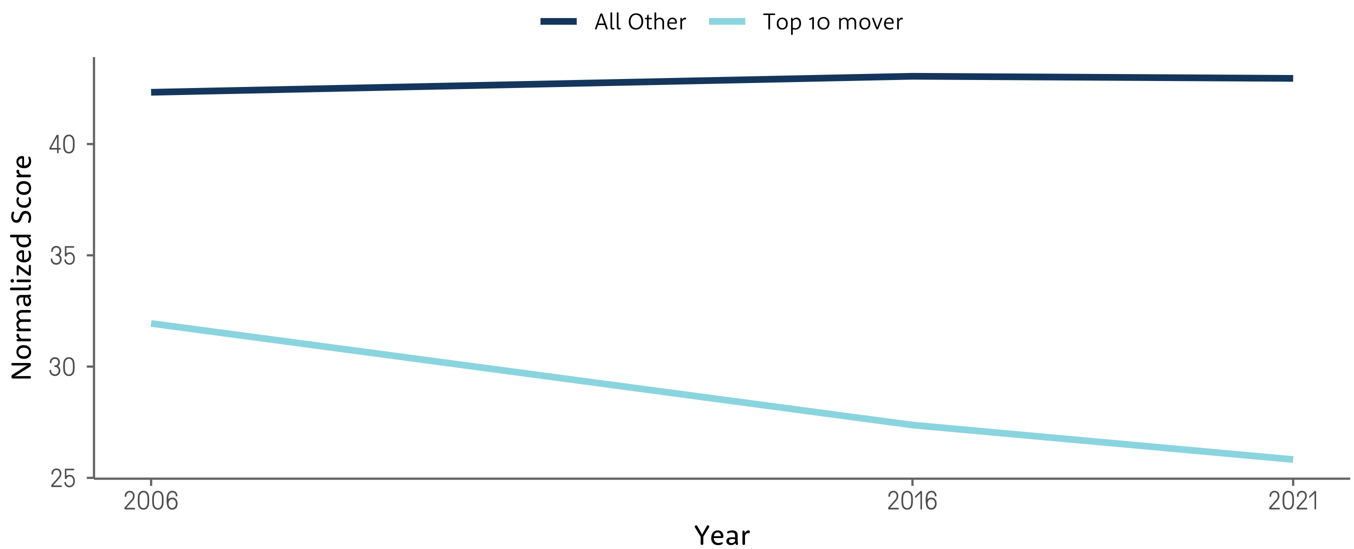
Figure 2

Work context—importance of repeating the same task—Canadian occupations 2006-2021



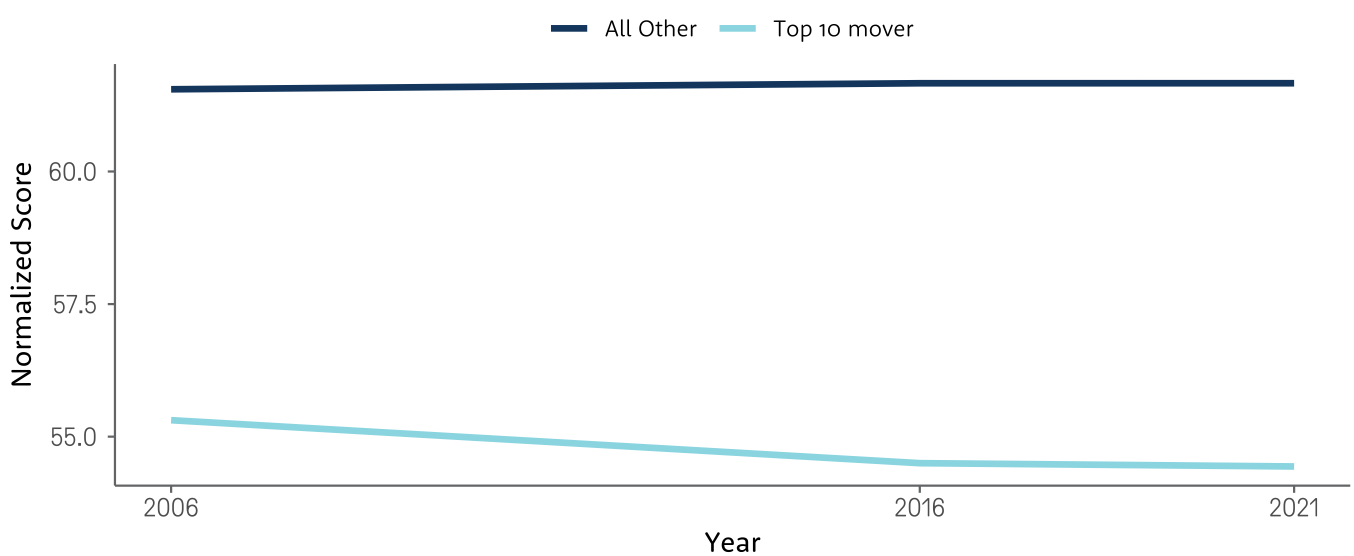
Source: O*Net, Author Calculations

Figure 3
Work context—pace determined by speed of equipment—Canadian occupations 2006-2021



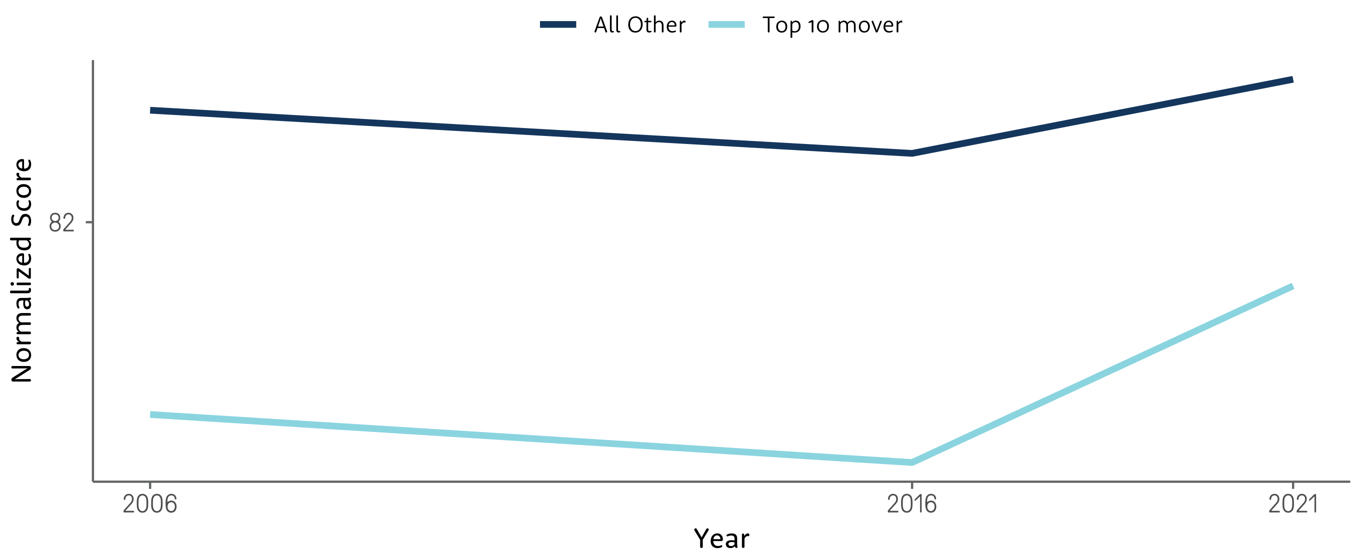
Source: O*Net, Author Calculations

Figure 4
Work context—spend time making repetitive motions—Canadian occupations 2006-2021



Source: O*Net, Author Calculations

Figure 5
Work context—importance of being exact or accurate—Canadian occupations 2006-2021



Source: O*Net, Author Calculations

Table 4
Top 10 movers from 2016 to 2021 (increased ranking in digital skills)

NOC title	Percentile in 2006	Percentile in 2016	Percentile in 2021
Photographic and film processors	31st	**30th**	**85th**
General practitioners and family physicians	40th	**16th**	**53rd**
Engineering inspectors and regulatory officers	74th	**20th**	**59th**
Health information management occupations	32nd	**47th**	**89th**
Railway carmen/women	71st	**22nd**	**50th**
Interior designers and interior decorators	85th	**51st**	**80th**
Other trades helpers and labourers	41st	**27th**	**65th**
Medical laboratory technologists	77th	**27th**	**56th**
Optometrists	45th	**35th**	**70th**
Wholesale trade (non-technical)	47th	**29th**	**57th**

When we focus on changes that occurred only in the past five years, between 2016 and 2021 (and thus more short-term technological changes–summarized in Table 4), a different pattern emerges. The top movers between 2016 and 2021 are occupations that had already been overwhelmingly non-routine. Acemoglu (2019) highlights that although technological progress eliminated many white-collar tasks, it has also led to the creation of many other tasks, including programming, design, and software development.

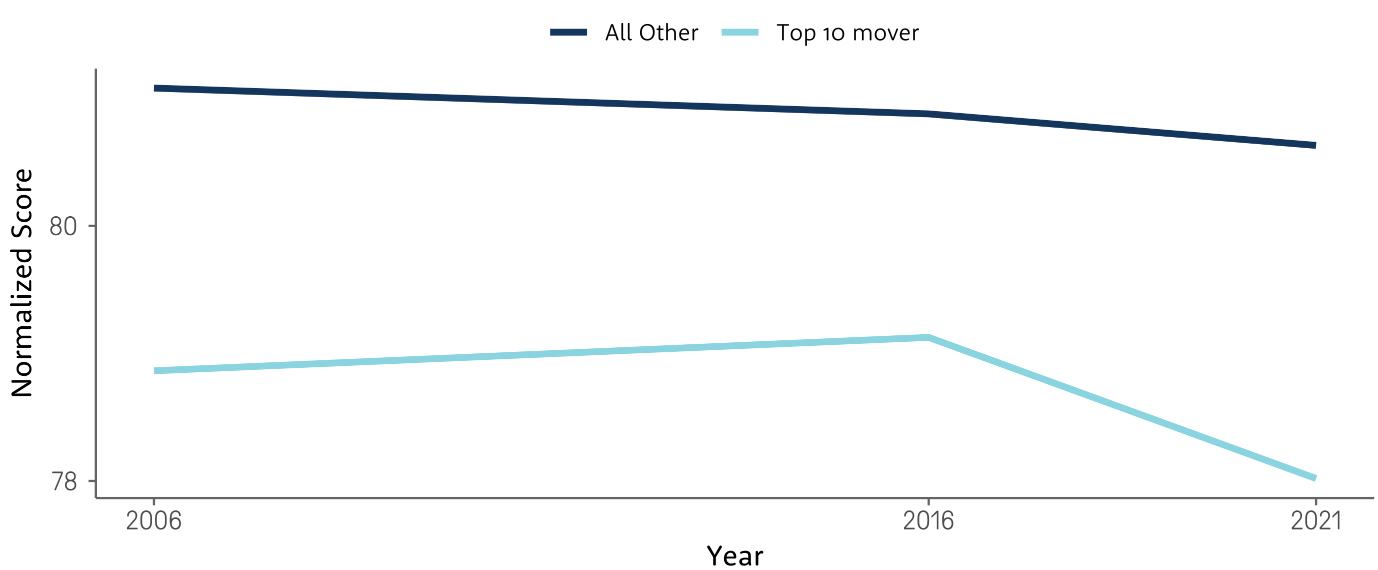
The top movers between 2016 and 2021 are occupations that had already been overwhelmingly non-routine.

Of the top ten, the normalized scores of health information management occupations increased the most in Engineering Design, Programming, and Computers and Electronics skills. Optometrists increased the most in "interacting with computers". Railway Carmen/women increased the most in Engineering and Technology. Engineering inspectors and regulatory officers increased the most in Telecommunications.

A similar analysis of changes in the work-contexts related to routine tasks for these occupations further characterize their differences compared to occupations that saw the highest level of digitalization between 2006 and 2021. Even as a baseline, these occupations often had lower scores than other occupations across all categories, with the gap growing even further between 2006 and 2021. Most interestingly, the normalized score related to being exact or accurate was initially higher in these occupations compared to others, but by 2021, the score was reduced to below levels seen by other occupations. This suggests that as more technology gets incorporated, these workers can afford to be less exact and have technologies correct for those small inaccuracies.

Figure 6

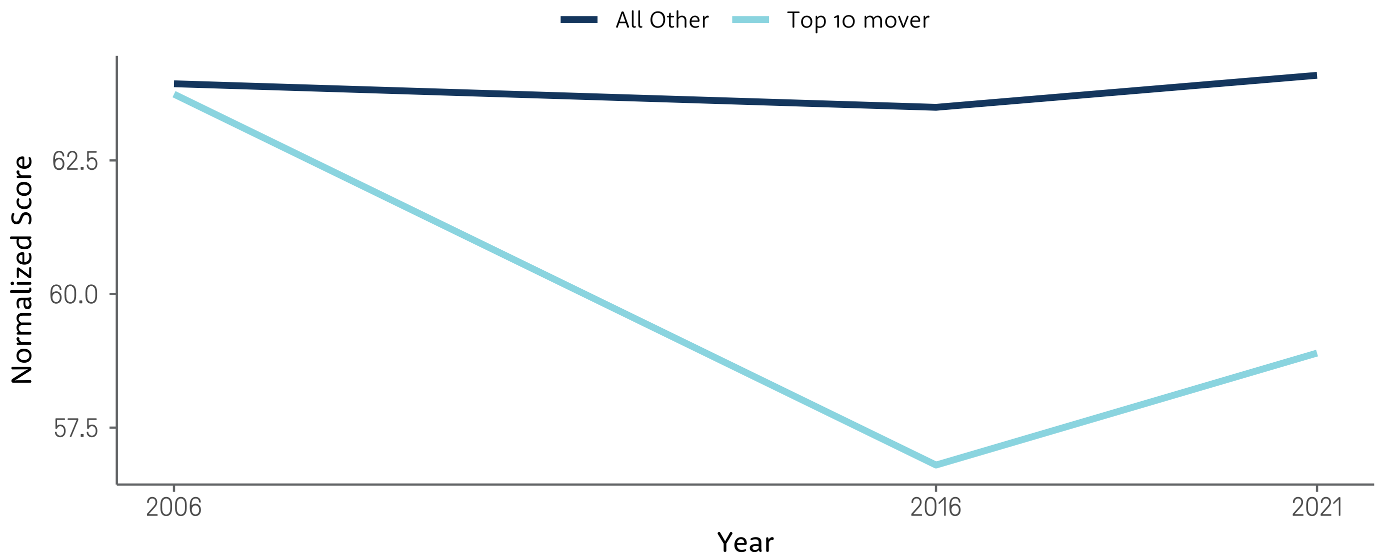
Work context—structured vs unstructured—Canadian occupations 2016-2021



Source: O*Net, Author Calculations

Figure 7

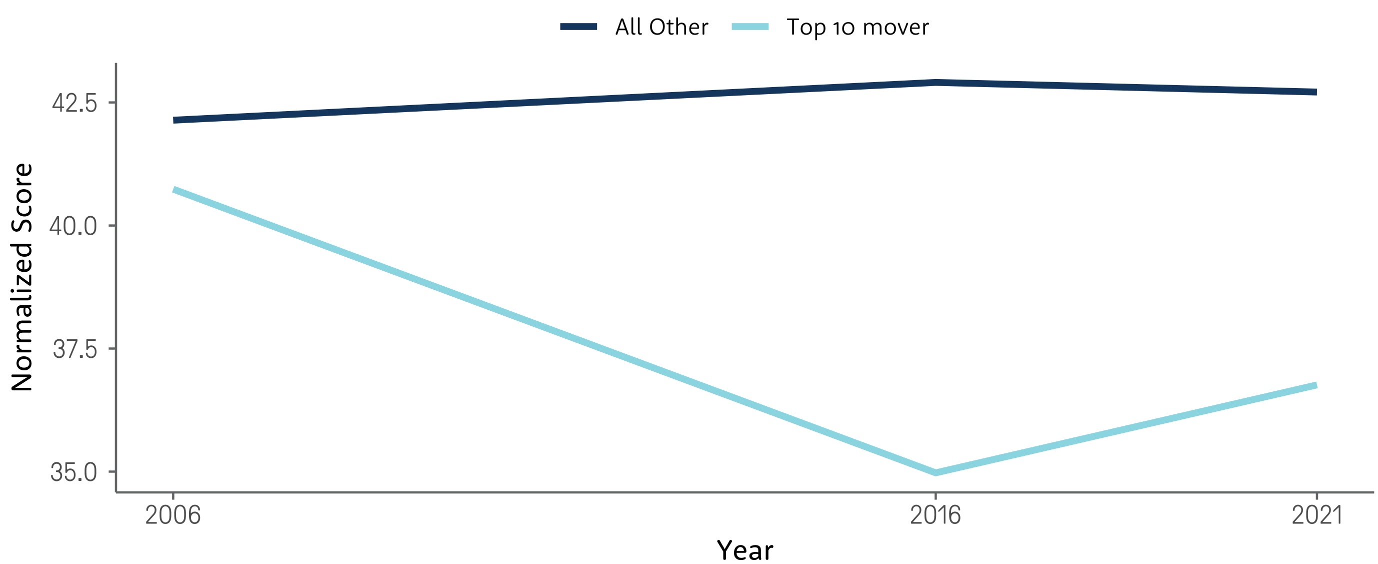
Work context—importance of repeating the same task—Canadian occupations 2016-2021



Source: O*Net, Author Calculations

Figure 8

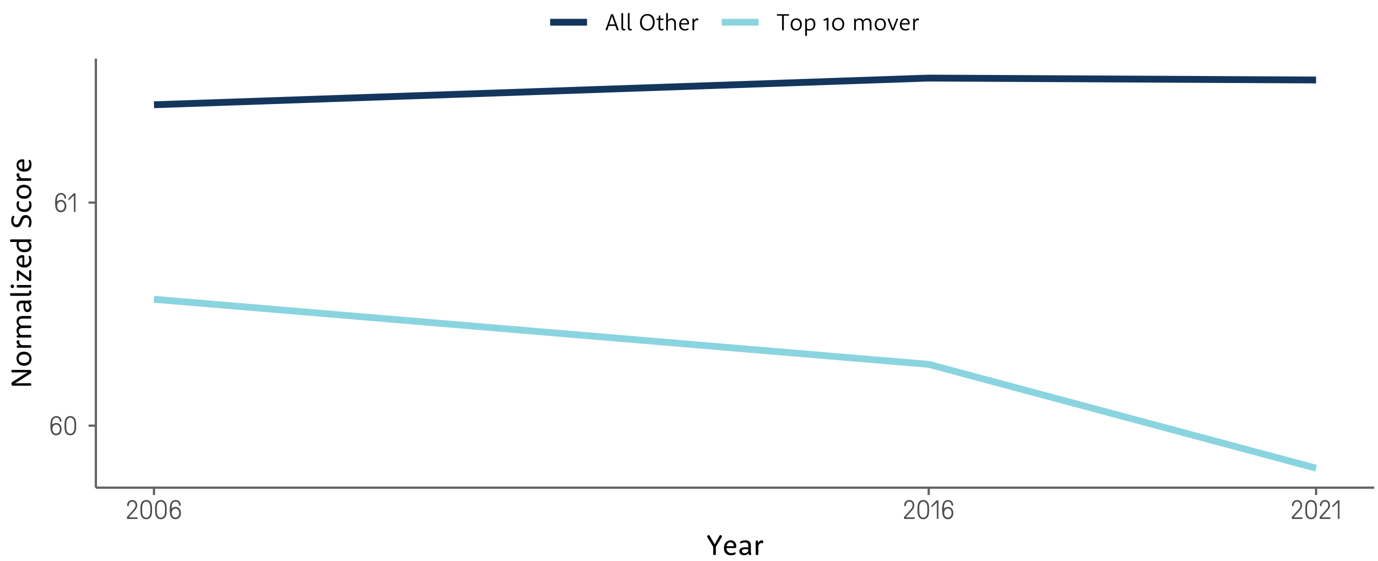
Work context—pace determined by speed of equipment—Canadian occupations 2016-2021



Source: O*Net, Author Calculations

Figure 9

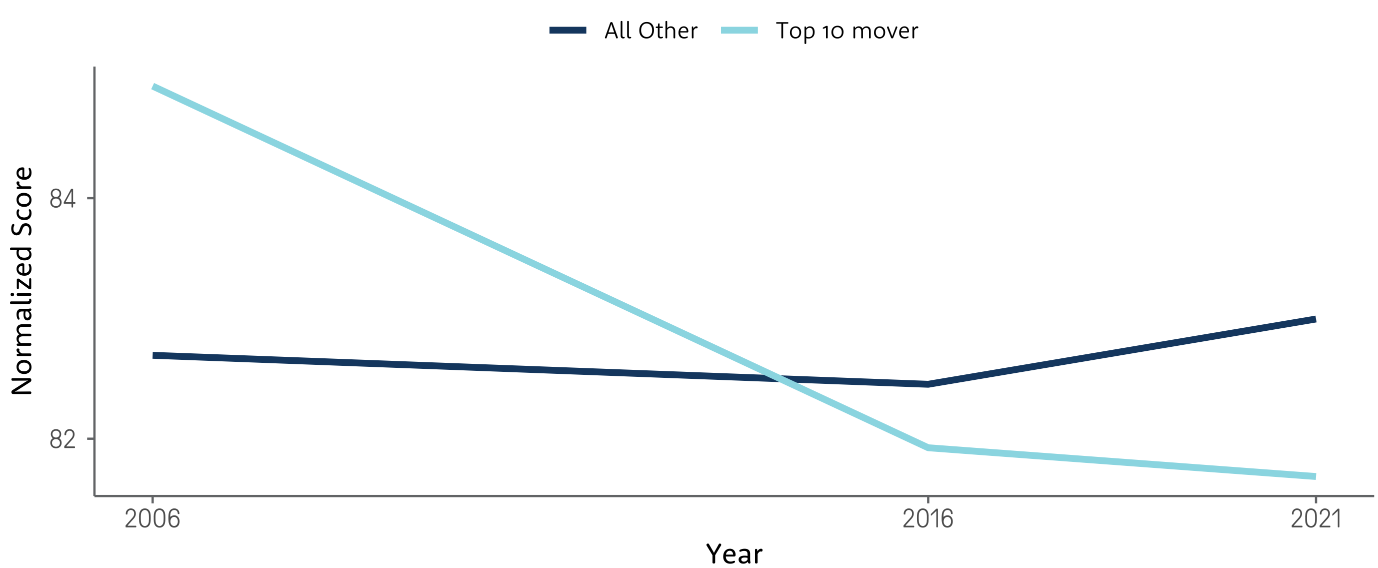
Work context—spend time making repetitive motions—Canadian occupations 2016-2021



Source: O*Net, Author Calculations

Figure 10

Work context—importance of being exact or accurate—Canadian occupations 2016-2021



Source: O*Net, Author Calculations

Stalled digital adoption in agriculture (fishing), and machine learning

Table 5 shows occupations that saw the slowest rate of digitalization compared to others between 2006 and 2021. As our study focuses on changes in percentiles, a drop does not indicate less technology is being used, but rather that the pace of digitalization has slowed compared to other occupations. Many of the jobs that saw a drop in their percentile rank during this period are jobs within the fishing and agriculture sectors. The agriculture sector especially is especially one that is known to continuously introduce and rely on new technologies. Fitzgerald (1991) describes major technological advancements in agricultural equipment and technology, and Gianinazzi et. al (2002) highlights major breakthroughs in soil biology and genetic engineering techniques. But the drop in ranking implies a slowdown in the pace of digital technology adoption relative to other occupations in the period between 2006 and 2016, which could indicate that the wave of digitalization happened earlier and there are less remaining technologies to be easily digitalized. This is a prime example of the fact that the comparison between

The drop in ranking implies a slowdown in the pace of digital technology adoption relative to other occupations in the period between 2006 and 2016, which could indicate that the wave of digitalization happened earlier and there are less remaining technologies to be easily digitalized.

Table 5

Top 10 movers from 2006 to 2021 (decreased ranking in digital skills)

NOC Title	Percentile in 2006	Percentile in 2016	Percentile in 2021
Waterworks and gas maintenance	**81st**	67th	**67th**
Transportation route and crew schedulers	**76th**	76th	**29th**
Fishing masters and officers	**72nd**	60th	**18th**
Fishermen/women	**72nd**	60th	**18th**
Fishing vessel deckhands	**72nd**	60th	**18th**
Machining tool operators	**87th**	34th	**29th**
Program officers unique to government	**69th**	27th	**23rd**
Chemical plant machine operators	**75th**	43rd	**31st**
Technical sales specialists—wholesale trade	**93rd**	76th	**33rd**
Managers in aquaculture	**94th**	72nd	**45th**

jobs in this case is best carried out in relative terms, and not absolute terms.

O'Donnell and Skuterud (2021) discuss the growth of temporary worker programs in the years from 2000 to 2019, which provided the agricultural sector with increasing numbers of low-cost labour through the Seasonal Agricultural Worker Program (SAWP). This could be a contributing factor in the plateau observed in the digitalization of agriculture, though unlikely to impact the fishing industry. In the years to come, this picture might change significantly, with studies like King (2017) discussing a future where agriculture is led by advances in robotics, and Usman et. al. (2020) discussing the role of the Internet of Things (IoT) in further modernizing the agriculture sector of tomorrow.

Biggest drop in digital skills from 2016 – 2021 for air pilots, flight engineers and flight instructors

Table 6 shows the same analysis for the period between 2016 and 2021. Air pilots, flight engineers, and flying instructors led the drop in ranking, moving from around the 87th percentile in 2016 to around the 38th percentile in 2021. Translators, terminologists, and interpreters had one of the highest upward movements in ranking between 2006 and 2016, adopting digital technologies including Computer Assisted Interpreter Training (CAIT) as described in Sandrelli and Jerez (2007). However, the pace of digital technological advancement slowed substantially afterwards, leading to a significant drop in ranking for the period between 2016 and 2021, and to several studies such as Sigacheva, Baranova, and Makaev (2021) discussing the need to further improve machine translation.

Table 6

Top 10 movers from 2016 to 2021 (decreased ranking in digital skills)

NOC title	Percentile in 2006	Percentile in 2016	Percentile in 2021
Air pilots, flight engineers, and flying instructors	76th	**87th**	**38th**
Fishing masters and officers	72nd	**60th**	**18th**
Fishermen/women	72nd	**60th**	**18th**
Fishing vessel deckhands	72nd	**60th**	**18th**
Paramedical occupations	57th	**83rd**	**37th**
Transportation route and crew schedulers	77th	**76th**	**29th**
Translators, terminologists and interpreters	16th	**69th**	**28th**
Library and public archive technicians	59th	**77th**	**33rd**
Security guards and related security service occupations	20th	**64th**	**24th**
Technical sales specialists—wholesale trade	93rd	**76th**	**32nd**

Fishing jobs continued the trend of falling in ranking during this period. Pratiwy, Cahya, and Andriani (2022) discuss the fact that since 1969, the fishing industry has been shifting towards digitalization, with the introduction of electronic tools and information technology, and the use of Global Positioning Systems (GPS). However, over the past two decades, this shift towards digitalization slowed significantly, leading to these large drops we observe in the ranking. Pratiwy, Cahya, and Andriani (2022) also discuss the fact that future fishing industries will need to make use of IoT and Cyber-Physical Systems (CPS), which involves integrating computing, sensing, and networks into physical objects, in order to prevent illegal, unreported and unregulated fishing, and to become more sustainable as an industry. In the Canadian context, recent federal investments in the Oceans Global Innovation Cluster (formerly Oceans Supercluster) shows the government's commitment to continue introducing technologies in this area of the economy.

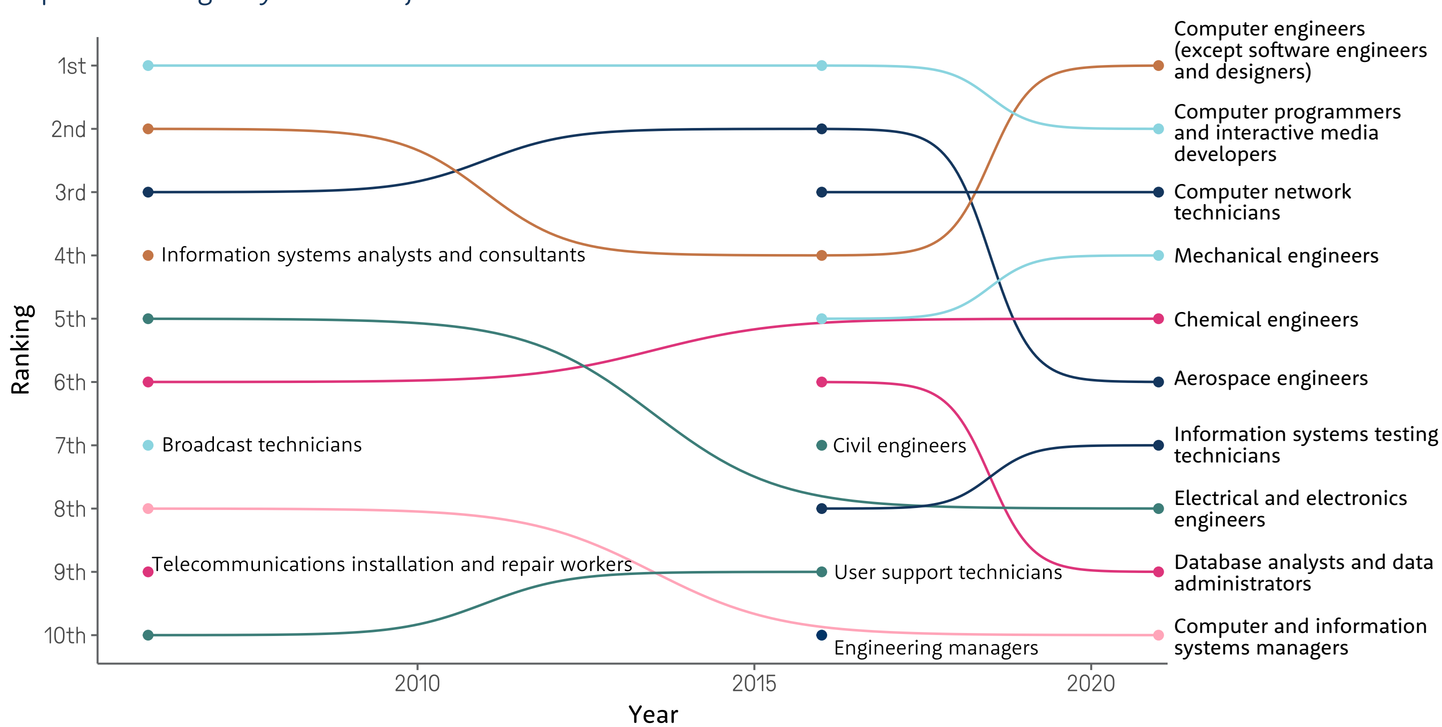
Persistence of highly digital occupations

While examining the changes in occupations that saw the largest shifts in relative digital intensity is important, our study is also interested in understanding whether the composition of occupations that are the most digital has shifted in the past 15 years.

Table 5 shows these top ten NOC titles in order, where Computer Programmers and Interactive Media Developers' maintained the lead in 2006 and 2016. While Telecommunications Installation and Repair Workers remained on the top ten list for those years, that classification has fallen out in 2021 dropping down to eleventh place. This table highlights the persistence of these top ten NOC occupations across the three years, reflecting an ongoing rapid wave of digitalization in these fields relative to many other occupations.

Figure 11

Top 10 most digitally intensive jobs



Source: O*Net, Author Calculations

Table 7

Top 10 occupations across 3 years

Top 10 NOC titles—2006	Top 10 NOC titles—2016	Top 10 NOC titles—2021
Computer programmers and interactive media developers	Computer programmers and interactive media developers	Computer engineers (except software engineers and designers)
Computer engineers (except software engineers and designers)	Aerospace engineers	Computer network technicians
Aerospace engineers	Computer network technicians	Computer programmers and interactive media developers
Information systems analysts and consultants	Computer engineers (except software engineers and designers)	Mechanical engineers
Electrical and electronics engineers	Mechanical engineers	Chemical engineers
Chemical engineers	Database analysts and data administrators	Aerospace engineers
Broadcast technicians	Civil engineers	Information systems testing technicians
Computer and information systems managers	Information systems testing technicians	Electrical and electronics engineers
Telecommunications installation and repair workers	User support technicians	Database analysts and data administrators
User support technicians	Engineering managers	Computer and information systems managers

Disaggregating changes by occupational skill levels

To further highlight the plateau effect discussed earlier (where in certain industries, such as in agriculture or interpretation, digital technology seems to advance quickly for a period of time before reaching a plateau), we focus on digital technology changes within different NOC skill categories. One of the main questions in the literature on digitalization and its effects on labour demand is whether advancements in digital technology would substitute for or complement labour in different industries and within different skill groups. Acemoglu and Autor (2011) discuss a canonical model where technology is assumed to complement high- and low-skilled workers, and offer an alternative task-based framework where technology, capital, and labour compete for certain tasks. These models suggest differential impacts of technology on different kinds of work activities.

In order to explore and elucidate some of these impacts, we rely on the fact that NOC divides occupations into five broad skill levels[3]. Skill level 0 is reserved for management jobs, such as restaurant managers, mine managers, or shore captains (fishing). Skill level A is for professional jobs that usually require a degree from a university, such as doctors, dentists, and architects. Skill level B is for technical jobs and skilled trades that typically require a college diploma or training as an apprentice, such as chefs, plumbers, and electricians. Skill level C is for occupations where workers can learn relatively quickly on the job through job specific training, without formal education credentials beyond a high school diploma, such as long-haul truck drivers, food and beverage servers, or industrial butchers. Finally, skill level D is for labour jobs that usually require only on-the-job training, even without any formal educational credentials, such as fruit pickers, cleaning staff, or oil field workers.

Given the NOC skills classifications and the tasks observed on the NOC for most of the jobs within these classes, the NOC skills can be linked to the Autor, Levy, and Murnane (2003) matrix in the following way:

Table 8

NOC Skill Levels and Broad Task Classifications

NOC skill level	Classification
0 and A	Non-routine cognitive
B	Routine/non-routine cognitive and non-routine manual
C and D	Non-routine and routine manual

Autor, Levy, and Murnane (2003) provide evidence that suggests that for the non-routine cognitive class, technology tends to complement workers. As for the routine cognitive and manual class, many of the jobs among this group likely advanced in ranking due to the integration of digital technology into tasks where improvements can occur in the middle of their task distributions, or what is known in the literature as “job polarization.”

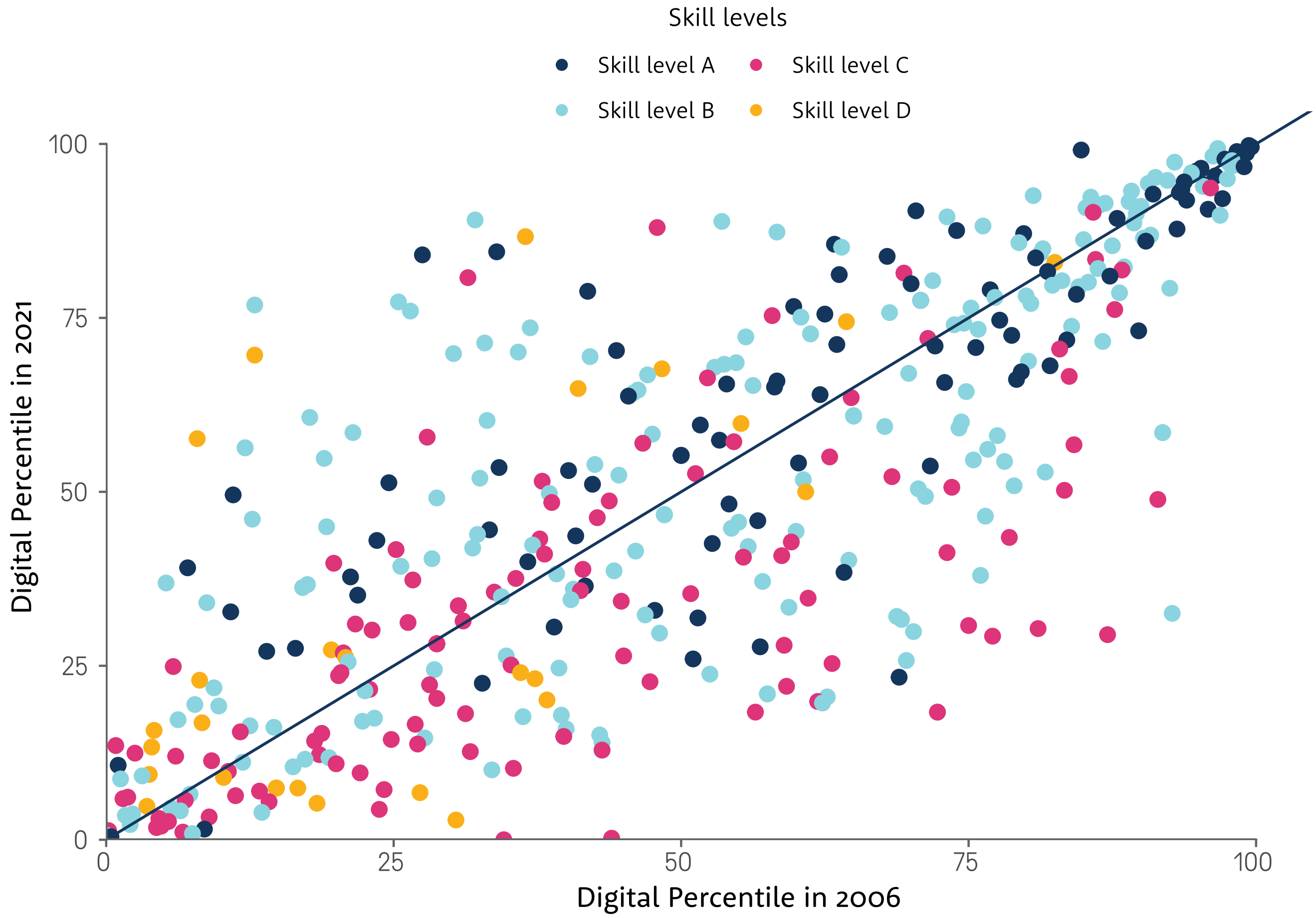
Finally, the non-routine manual is a class where technology plays a minor role, and therefore neither complements, nor substitutes for workers. Understanding changes within these skill groups can therefore help shape more heterogeneous policies for different workers across different industries where the most digital technology change is happening. We therefore see value in delineating the degree of technical change for each of these skill levels.

Looking at broad trends, the majority of occupations in skill level A (management and professional occupations) saw a rise in their digital intensity in the 15-year period covered in this study.

Looking at broad trends, the majority of occupations in skill level A (management and professional occupations) saw a rise in their digital intensity in the 15-year period covered in this study. Occupations in skill level B saw the largest variance, where half saw their digital intensity rise and half did not. Those working in occupations in skill levels C and D largely saw a decline in their digital intensity over the period.

When we look at the top occupations for each skill group, many of the top movers among skill level A are healthcare-related professions, which, as mentioned earlier, had seen an overall increase in demand for digital skills. By exploring the tasks for these jobs in the NOC, we observe that utilities managers likely gained a lot more digital skills in tasks where they analyze data, trends, reports, or test results to determine the adequacy of facilities. Lawyers likely need to employ databases more and use different digital tools to enhance their search for public and other legal records. Occupational therapists likely use digital tools to plan and organize occupational therapy programs, and to complete and maintain necessary records.

Figure 12
Digital intensity change 2006-2021 by skill levels



Source: O*Net, Author Calculations

Of the overall top ten movers in Table 1, five NOC titles had belonged to skill group B. This shows that many of the digital skill demand increases for the period between 2006 and 2021 had been in jobs that require college education or postsecondary training or apprenticeship.

Finally, with few exceptions, most of the top 10 increases in skill groups C and D had not led to major jumps in ranking, with many of the jobs that increased in ranking remaining closer to the bottom of the occupational distribution. This was expected, given that these skill groups belong to the non-routine manual classification, where technology plays a minor role.

As a final piece of analysis, we were interested in gaining a deeper understanding of how each of the six occupational factors we look at contributed to the changes that we observe. For example, were the movement driven more by changes (positive or negative) in specific occupations along one specific skill domain as opposed to another? To assess this, we analyzed how variations in one skill category impacted the overall change in digital intensity percentile.

As can be seen in Figures 13-18 and Table 9, variations in four skills stood out as being important in the changes in digital intensity seen in occupation. In particular, higher levels of variations in both programming and technology design were associated with an improvement in relative digital intensity over the 15-year period. Interestingly, higher variations in the "interacting with computers", as well as "computer and electronics" dimensions were associated with a decline in relative digital intensity over the same period. This is further suggestive of polarization trends that see automation technology, in specific occupational contexts, take away the need for workers to engage directly with technology.

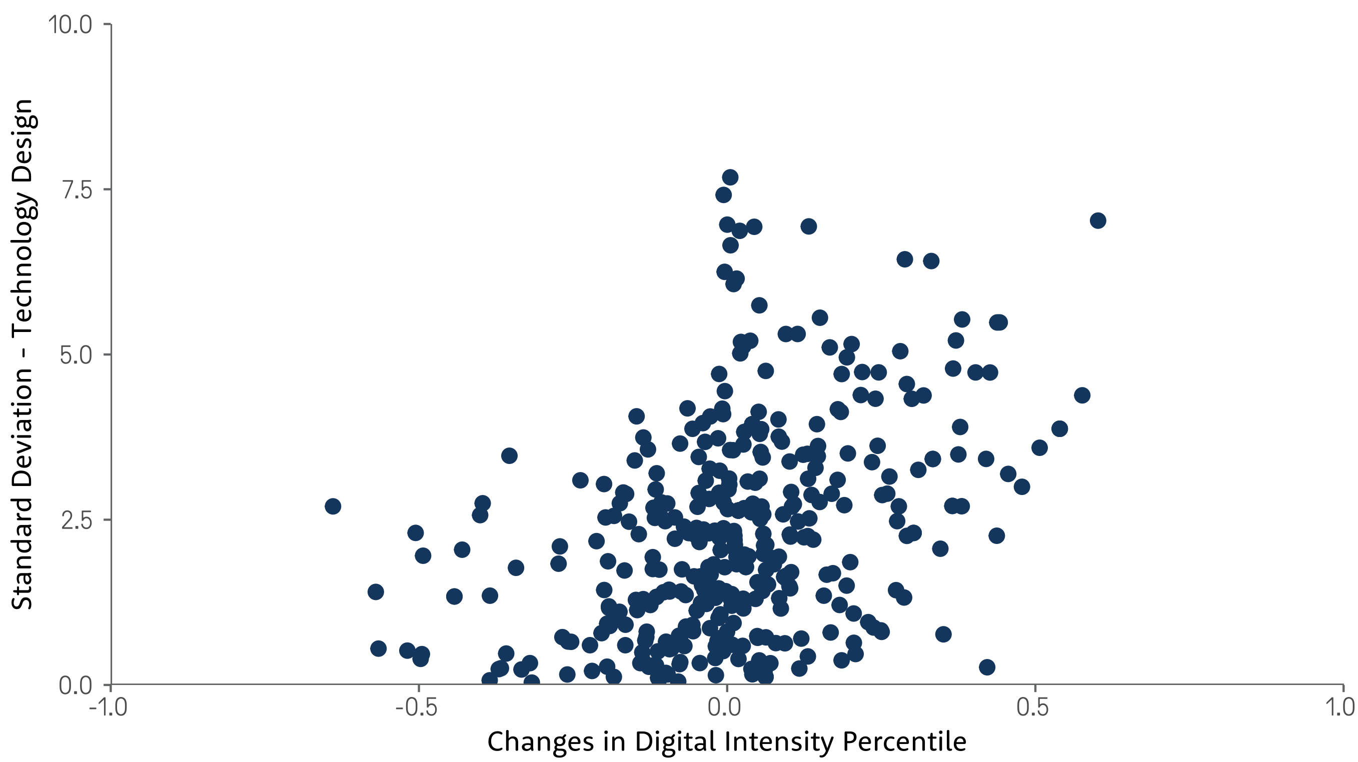
Table 9

Impact of variations in occupational attributes on digital intensity

Occupational attribute	Impact of variation on change in digital intensity **(bolded means statistically significant)**
Interacting with computers	**-2%**
Computer and electronics	**-3.2%**
Engineering and technology	-0.7%
Telecommunications	0.5%
Technology design	**4.7%**
Programming	**2.8%**

Figure 13

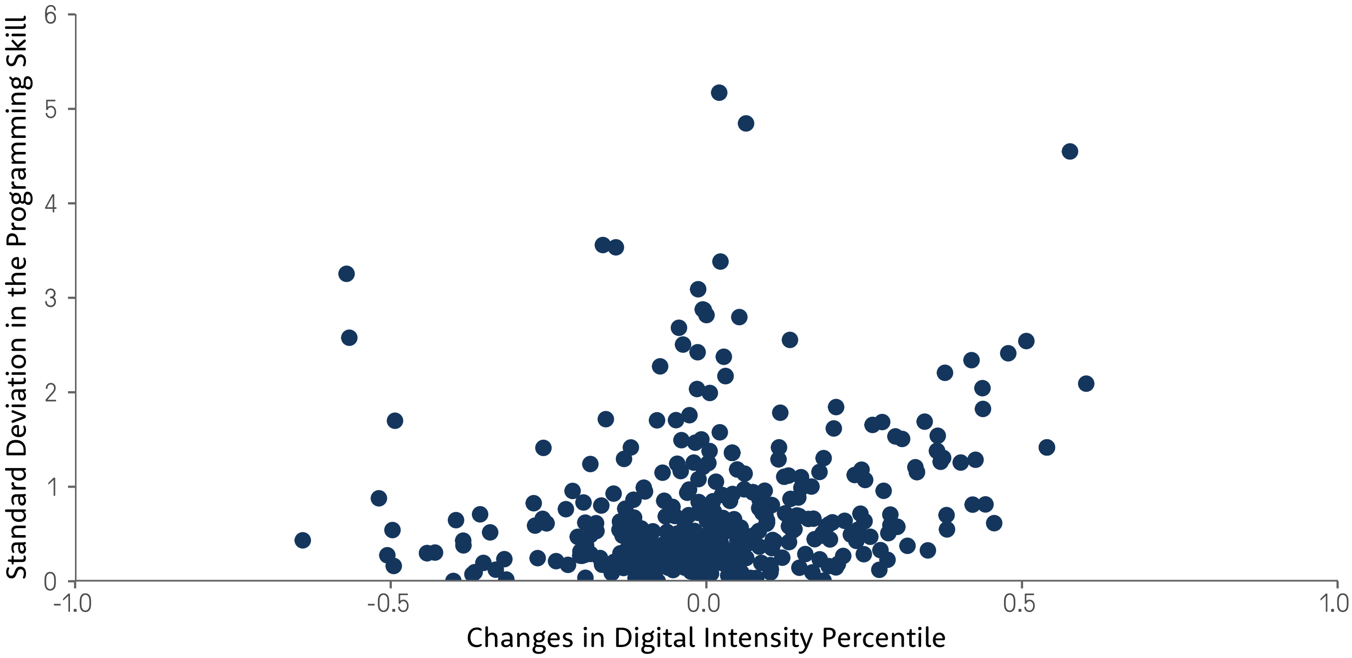
Variance in Technology Design Score for Canadian Occupations 2006-2021



Source: Author Calculations

Figure 14

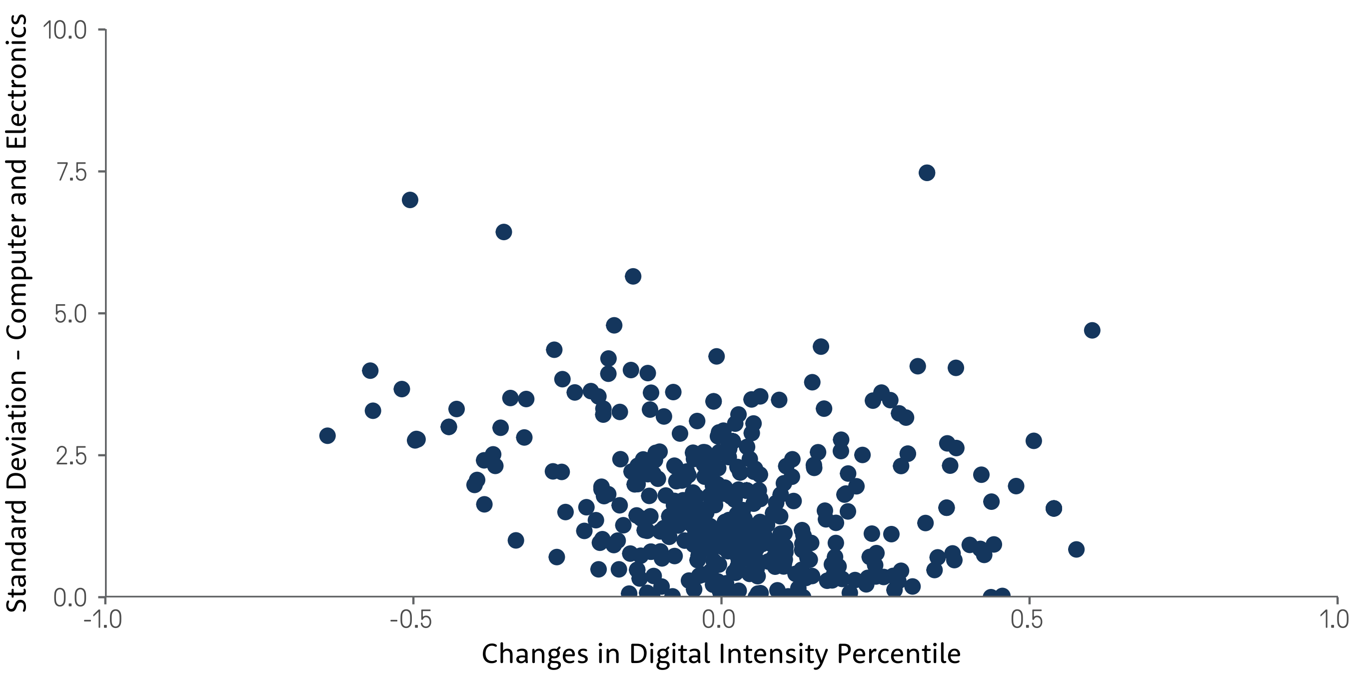
Variance in Programming Score for Canadian Occupations 2006-2021



Source: Author Calculations

Figure 15

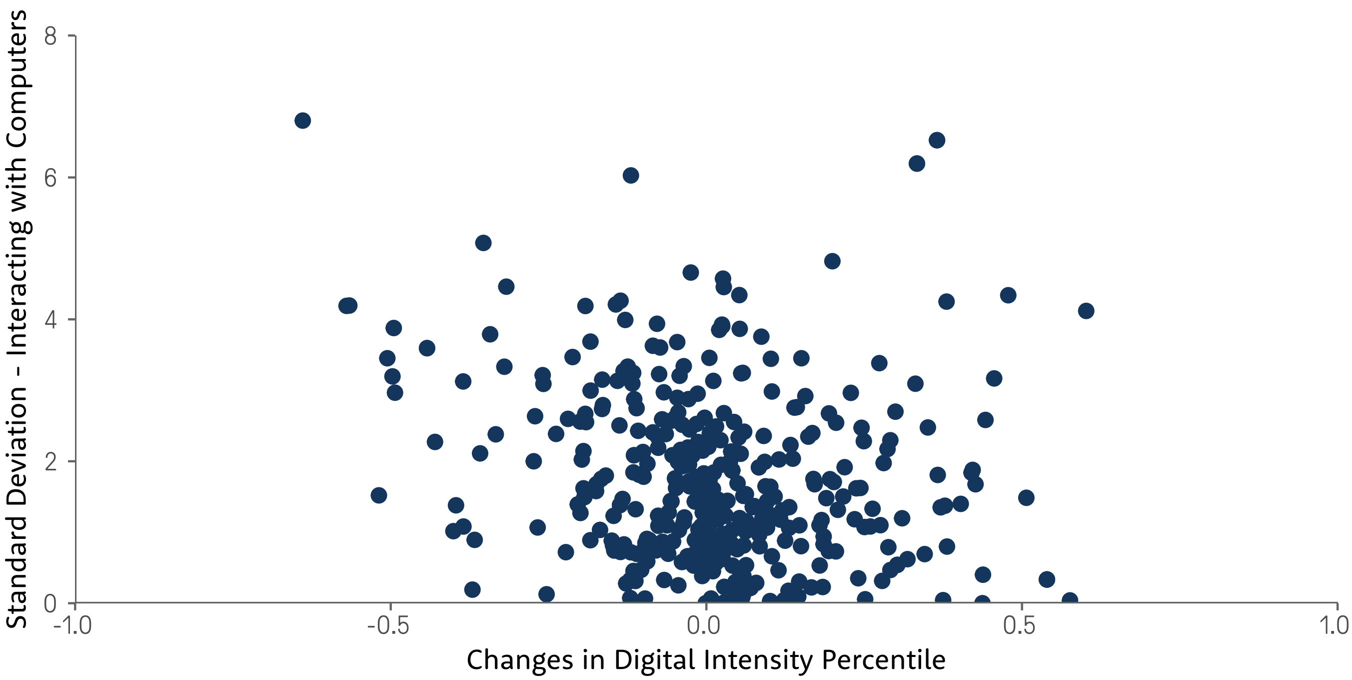
Variance in Computer & Electronics Score for Canadian Occupations 2006-2021



Source: Author Calculations

Figure 16

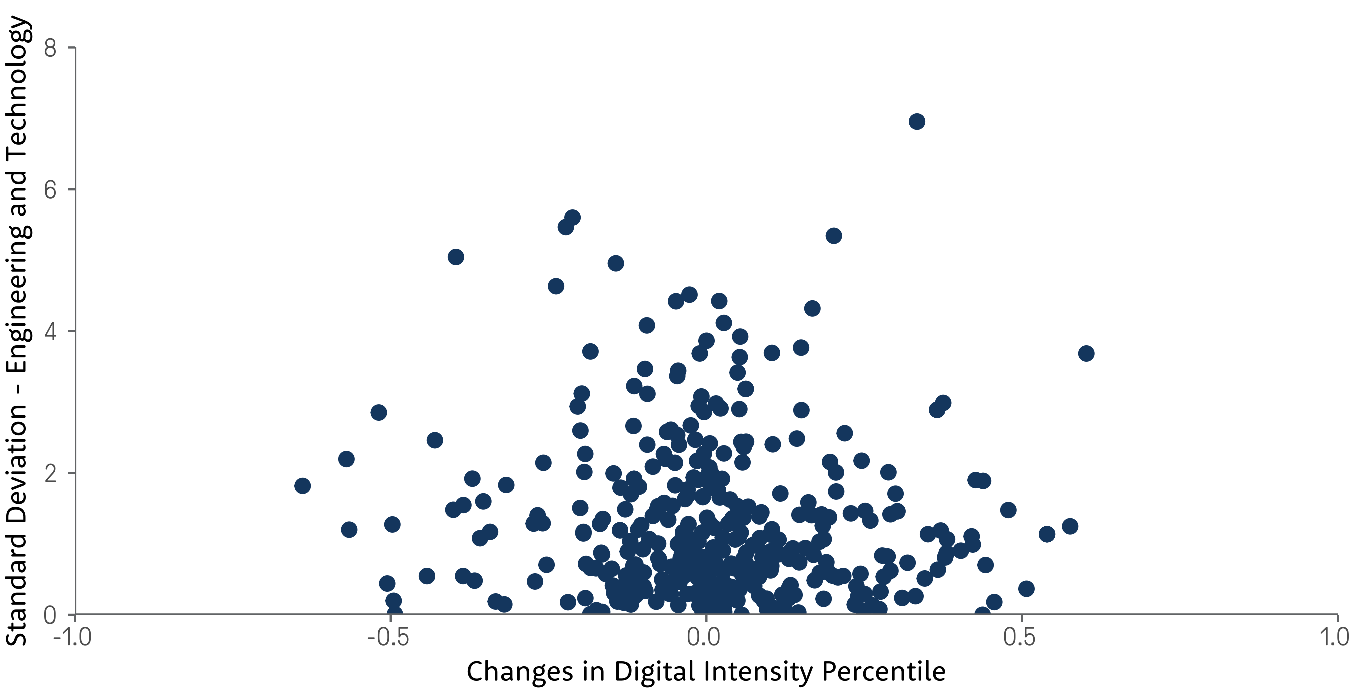
Variance in Interacting with Computers Score for Canadian Occupations 2006-2021



Source: Author Calculations

Figure 17

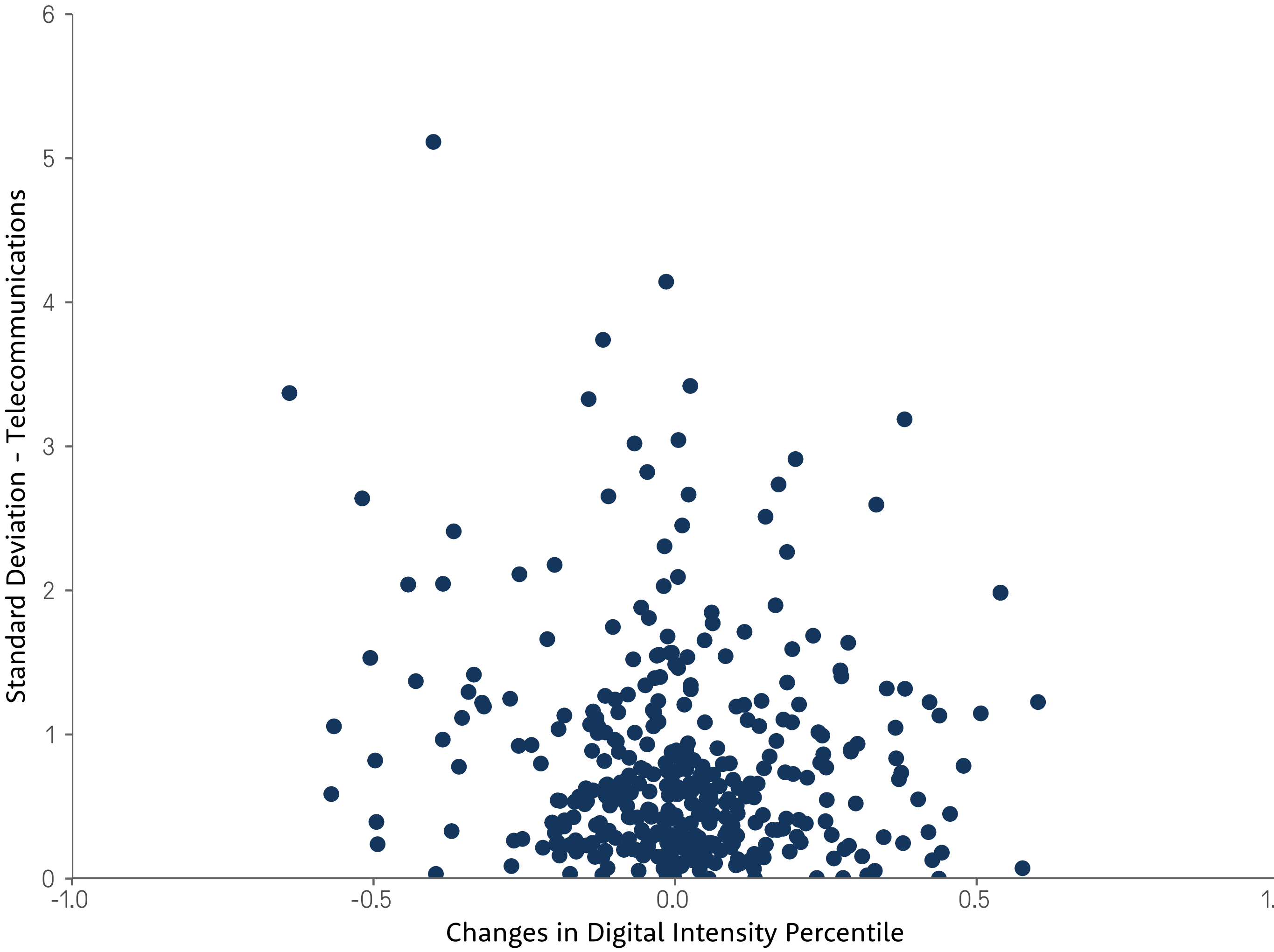
Variance in Engineering & Technology Score for Canadian Occupations 2006-2021



Source: Author Calculations

Figure 18

Variance in Telecommunications Score for Canadian Occupations 2006-2021



Source: Author Calculations

Conclusion

WITH MORE INNOVATION and advancement in digital technology expected in the coming years, the need to assess the movements in demand for digital skills in different Canadian jobs in the twenty-first century is growing ever more important. Cloud computing, artificial intelligence, the Internet of Things (IoT), and big data are among the growing and expanding innovations in digital technology that are expected to cause disruptions in global economies in the years ahead. Understanding labour skill demands and their movements and patterns over the years can be crucial to preparing Canadian workers for the upcoming waves of digitalization.

The data provides evidence that over the past 15 years, jobs that entail more routine tasks had overwhelmingly gained when it comes to digital advancements, compared to all other jobs. This included property administrators, railway conductors, and health information management occupations. However, the data also indicates that if we focus solely on the last five years, non-routine jobs have been the ones leading these changes, with large increases across all digital knowledge and skill scores.

The data provides evidence that over the past 15 years, jobs that entail more routine tasks had overwhelmingly gained when it comes to digital advancements, compared to all other jobs.

On the other hand, we found that many of the jobs that had been decreasing in ranking over the past 15 years had actually been jobs that already witnessed large improvements in digital technology, before reaching a plateau. This phenomenon was discussed in regards to agriculture jobs, where implementation of digital technologies had been relatively higher before 2006. It also points towards an important image: technology adoption is not only about the latest technology available (or could potentially be developed) to aid the work in a job, but rather depends on multiple factors, including availability and costs of labour.

In order to further explore the plateau effect and by employing the Autor, Levy, and Murnane (2003) framework on complementarity and substitution, we looked at changes in digital technology across different NOC skills groups. While technology is understood to generally complement the non-routine cognitive class, it likely replaces worker tasks in the routine cognitive and manual class, often in the middle of their task distributions. Finally, technology often plays no role in the non-routine manual class, neither complementing nor substituting workers. This was confirmed in the data, with minimal changes in the digital ranking of jobs in this class.

Overall, the top ten most digitalized jobs in 2006 have not been changing a lot over the past 15 years, with minor rank changes in 2016 and 2021 among them. The persistence of these jobs among the top of the list came as a result of high scores in Engineering Design, Engineering and Technology, and Programming. Indeed, five of these persistent top ten jobs are engineering job titles, leading the progress in digital technology.

Finally, we explored how each of the six occupational factors contributed to the change in digital intensity observed between 2006 and 2021 (which had been overwhelmingly routine jobs). We saw that occupations that saw higher variation in interacting with computers, as well as computer and electronics, saw a relative decline in digital intensity, while those that experienced large variations in skill requirements in programming as well as technology design, saw a rise in digital intensity, further confirming the hypothesis of occupational polarization along the routine-non-routine spectrum. Malleability, critical thinking, and knowledge across skills, is becoming ever more important to ensure workers can work alongside the digital technologies of tomorrow.

In the last five years, however, non-routine jobs have been the ones leading these changes, with large increases across all digital knowledge and skill scores.

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Endnotes

1 Harmonic mean is a type of average calculated for our data—the mean calculates the inverse of the mean calculated for the reciprocals of each value. The average is used because it is less sensitive to the existence of prominent values, and weighs the meric more towards consistency.

2 Min-max feature scaling is a method to normalize a set of data on a specified interval [0-1]. It is calculated by subtracting the minimum data point of the set from each point in the data, and dividing by the difference between the maximum data point and the minimum data point in the set.

3 It is important to note that these skill levels do not suggest a hierarchy of skills, but generally categorize the level of preparations (in terms of formal credentials or years of experience) in performing these jobs.

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